DFT models

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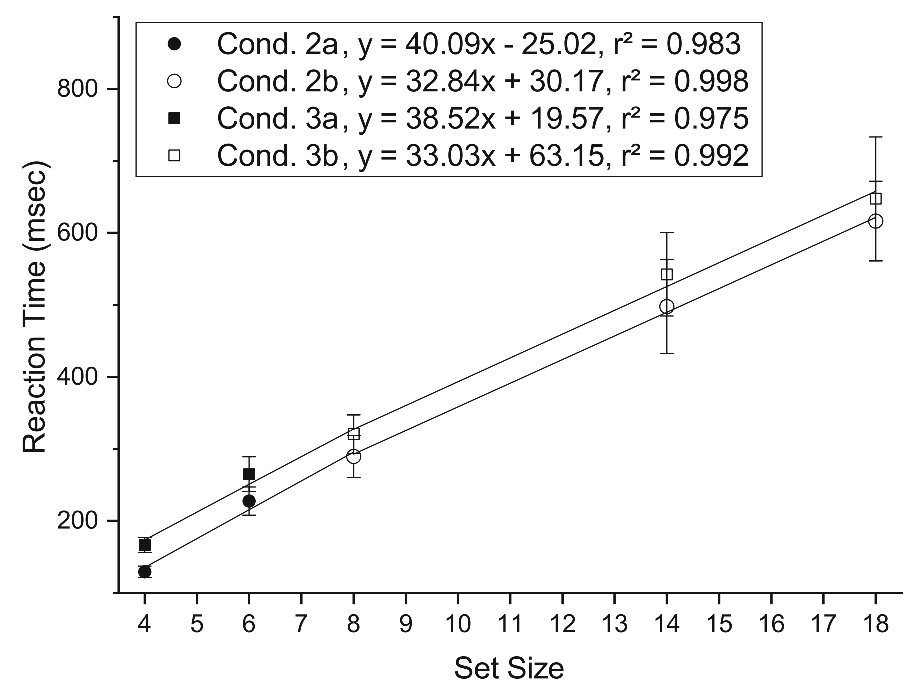
DFT models

- neural process models of sensori-motor behavior and cognition
- a spectrum of models that vary in how close and realistic the link to the sensory and motor surfaces is..
- => different interfaces to experimental observation

DFT models that account for behavior

- by mapping states of the model onto behavioral states/ measures
- example: RT
  - map experimental conditions onto sets of inputs and their time structure
  - in experiment, measure time to initiation of movement (reaction time) and compare in model to time for activation to reach a criterion level



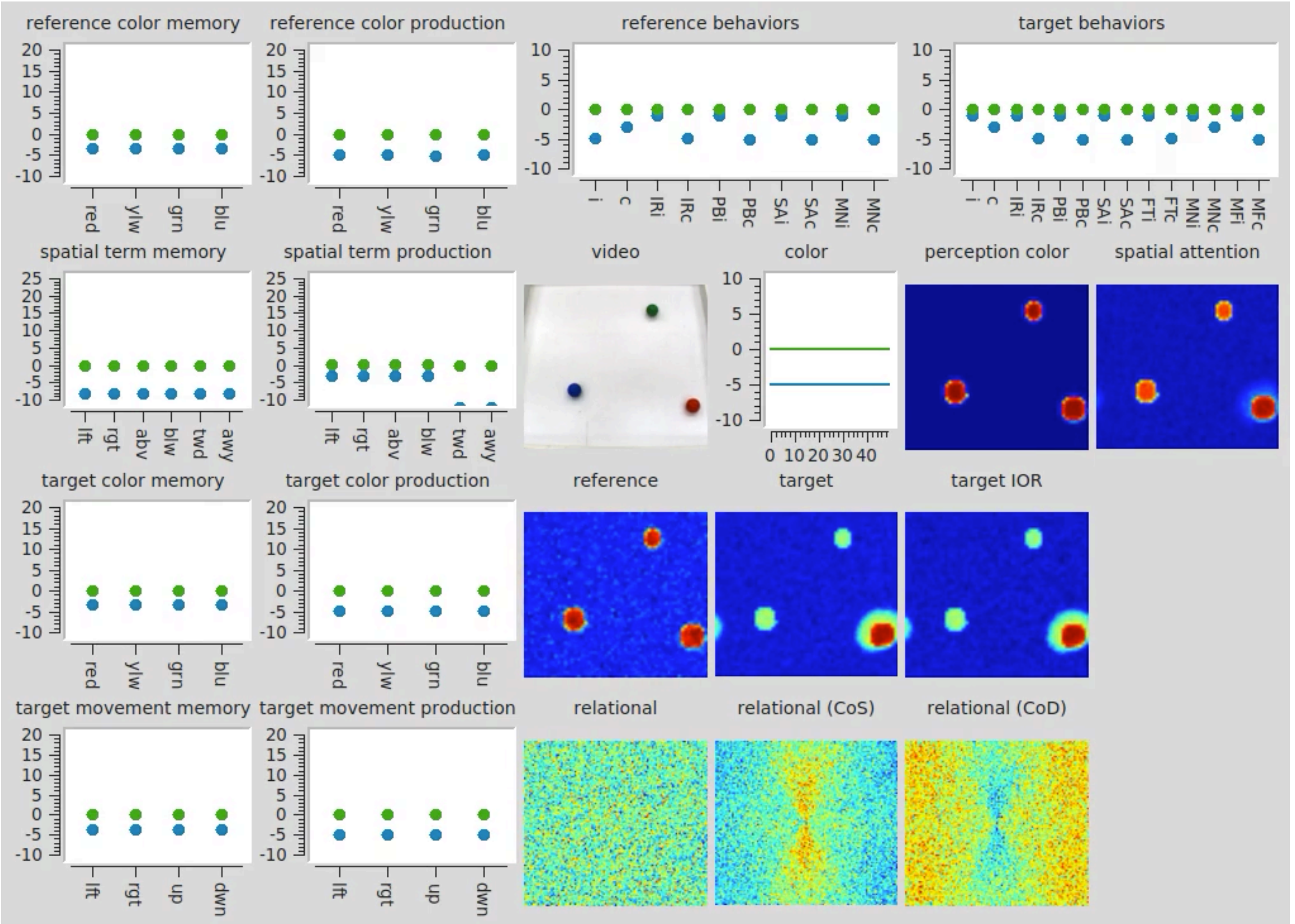
[Grieben et al. *Attention, Perception & Psychophysics* (2020)]

DFT models that account for behavior

- => I will lecture about that now

DFT models that account for behavior

- by linking DFT models to realistic sensor/motor models
- example: relational cognition: video input => categorical decisions



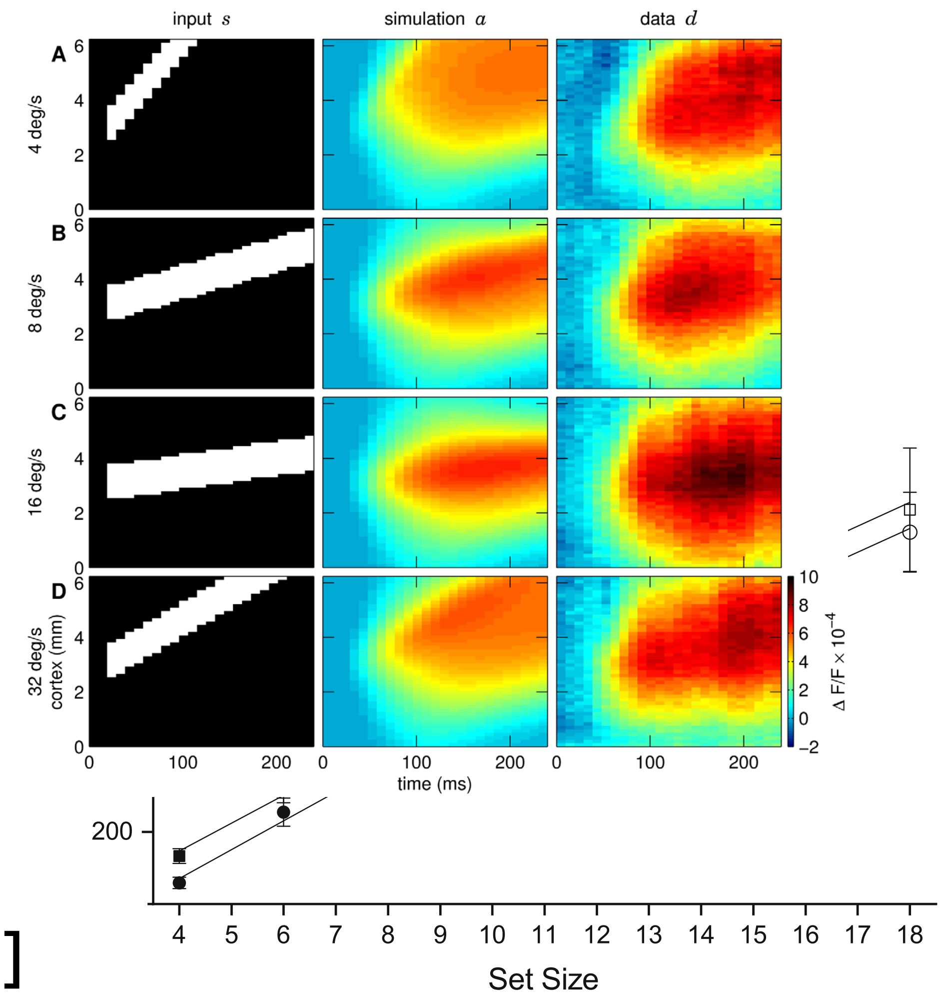
[Richter et al. *TopiCS*(2017)]

DFT models that account for behavior

- by linking DFT models to realistic sensor/motor models
- => lectures by Raul Grieben, Mathis Richter

DFT models that account for neural data

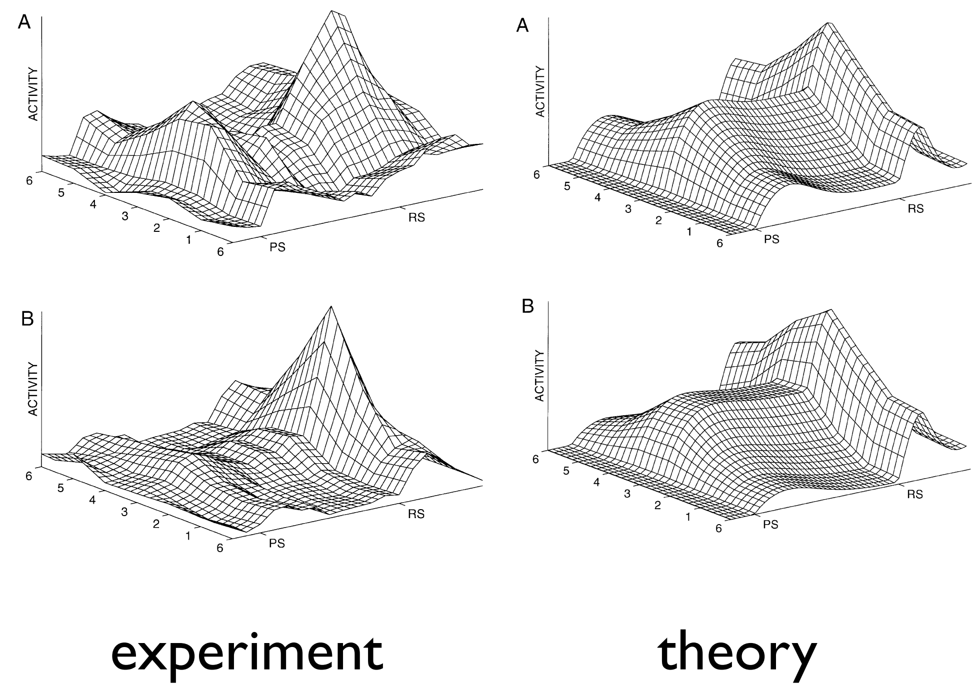
- by mapping states of the model onto neural measures
- example:
    - time courses of voltage-sensitive dye imaging on visual cortex



[Markounikau et al, *PLoS Comp Biol* (2010)]

DFT models that account for neural data

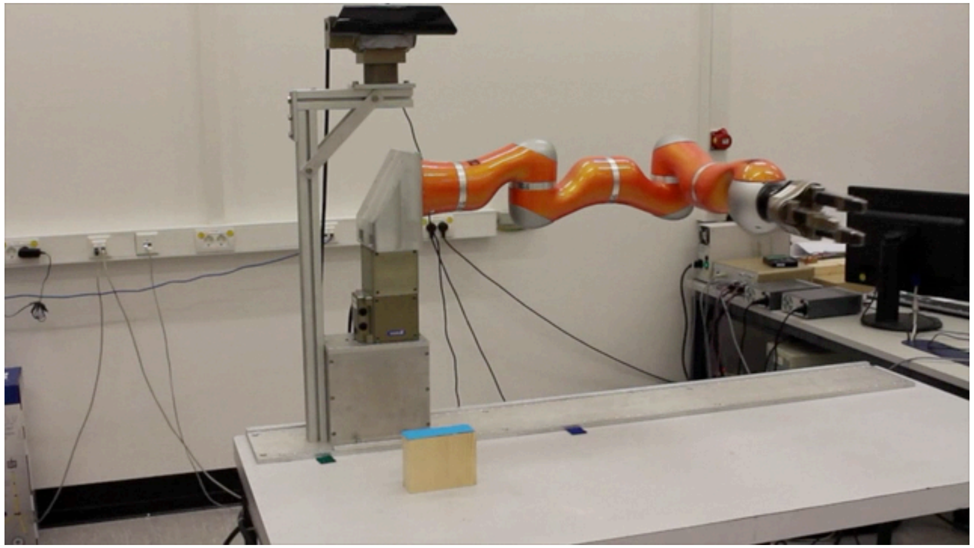
- I touched upon this briefly, will not expand
- => current work by John Spencer, Aaron Buss and others



[Bastian, Riehle, Erlhagen, Schöner, 98]

DFT models that account for behavioral competences

- by linking DFT models to real sensors/motor systems
- example: online updating
  - DFT model receives camera input
  - and drives a robotic arm
  - DFT model solved numerically on computers in real time
  - a real scenario emulates "online updating" of movement



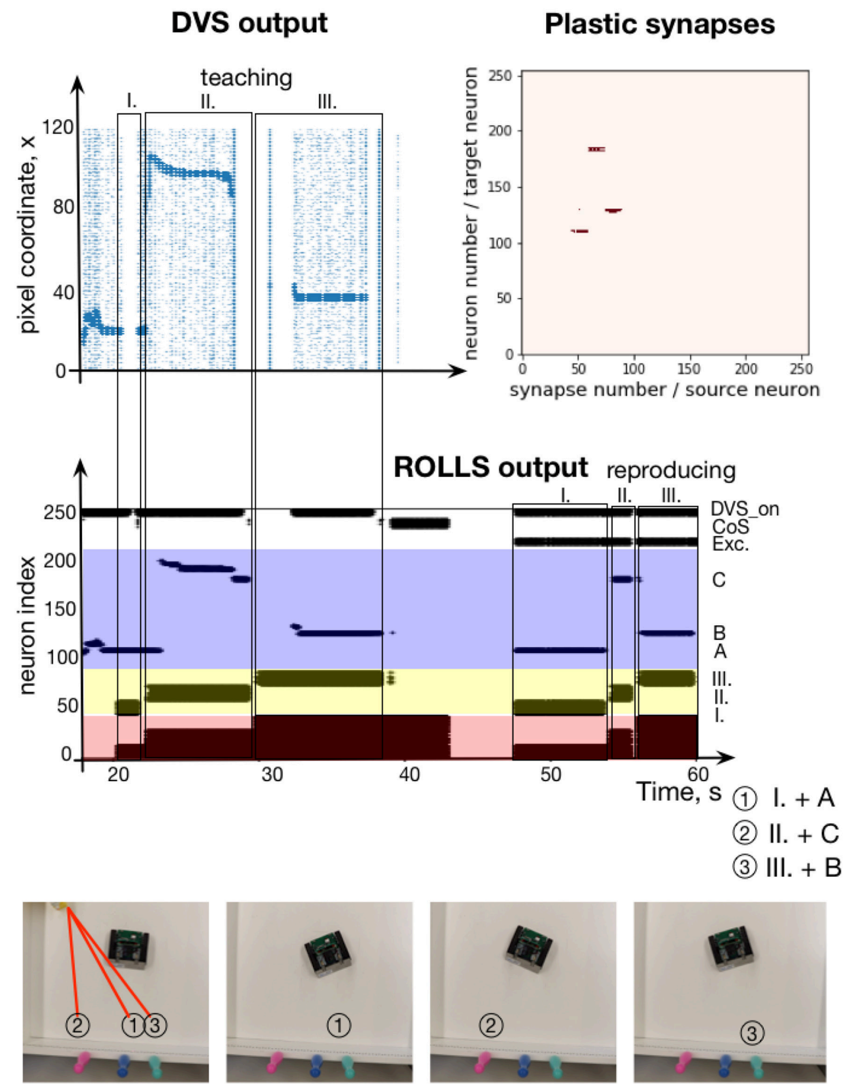
[Knips et al., *Frontiers Neurorobotics* (2017)]

DFT models that account for behavioral competences

- by linking DFT models to real sensors/motor systems
- => lecture by Jan Tekülve

DFT models that account for neural processes and behavioral competences

- by implementing DFT models directly on neuromorphic hardware and link it to real sensors/motor systems and
- example: sequence generation on vehicle
  - event based camera
  - drives vehicle
  - DFT model on neuromorphic chip



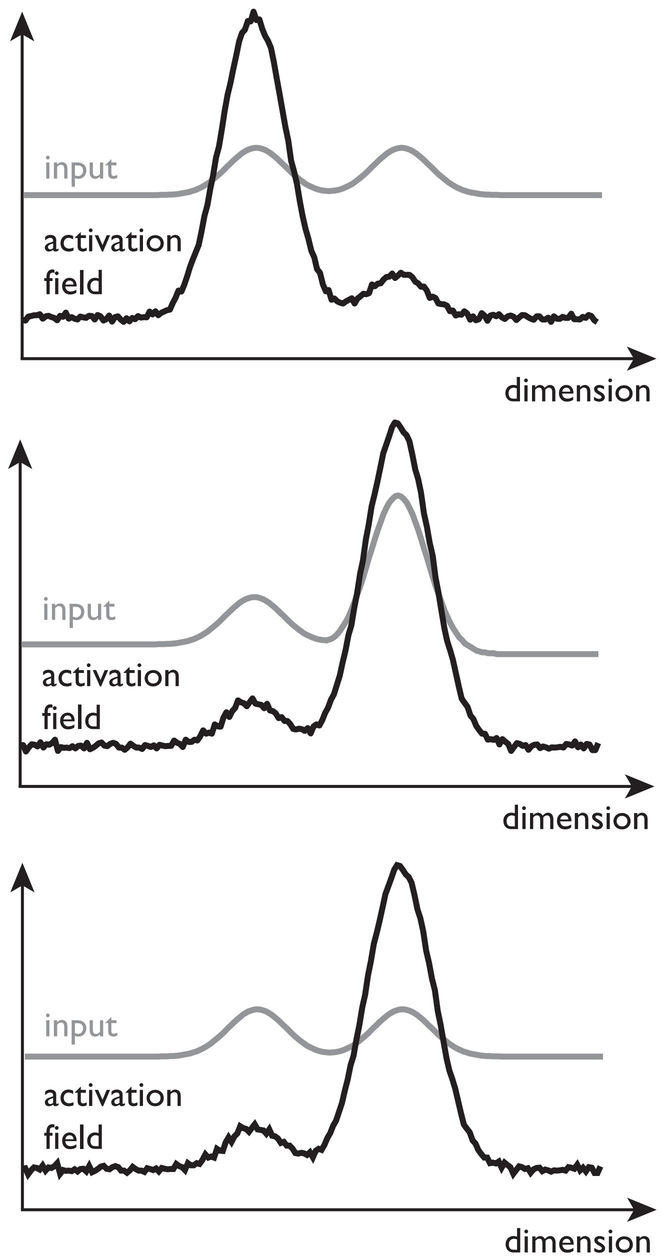
[Kreiser et al., *Frontiers Neuroscience* (2018)]

DFT models that account for neural processes and behavioral competences

- by implementing DFT models directly on neuromorphic hardware and link it to real sensors/motor systems and
- => lecture by Yulia Sandamirskaya

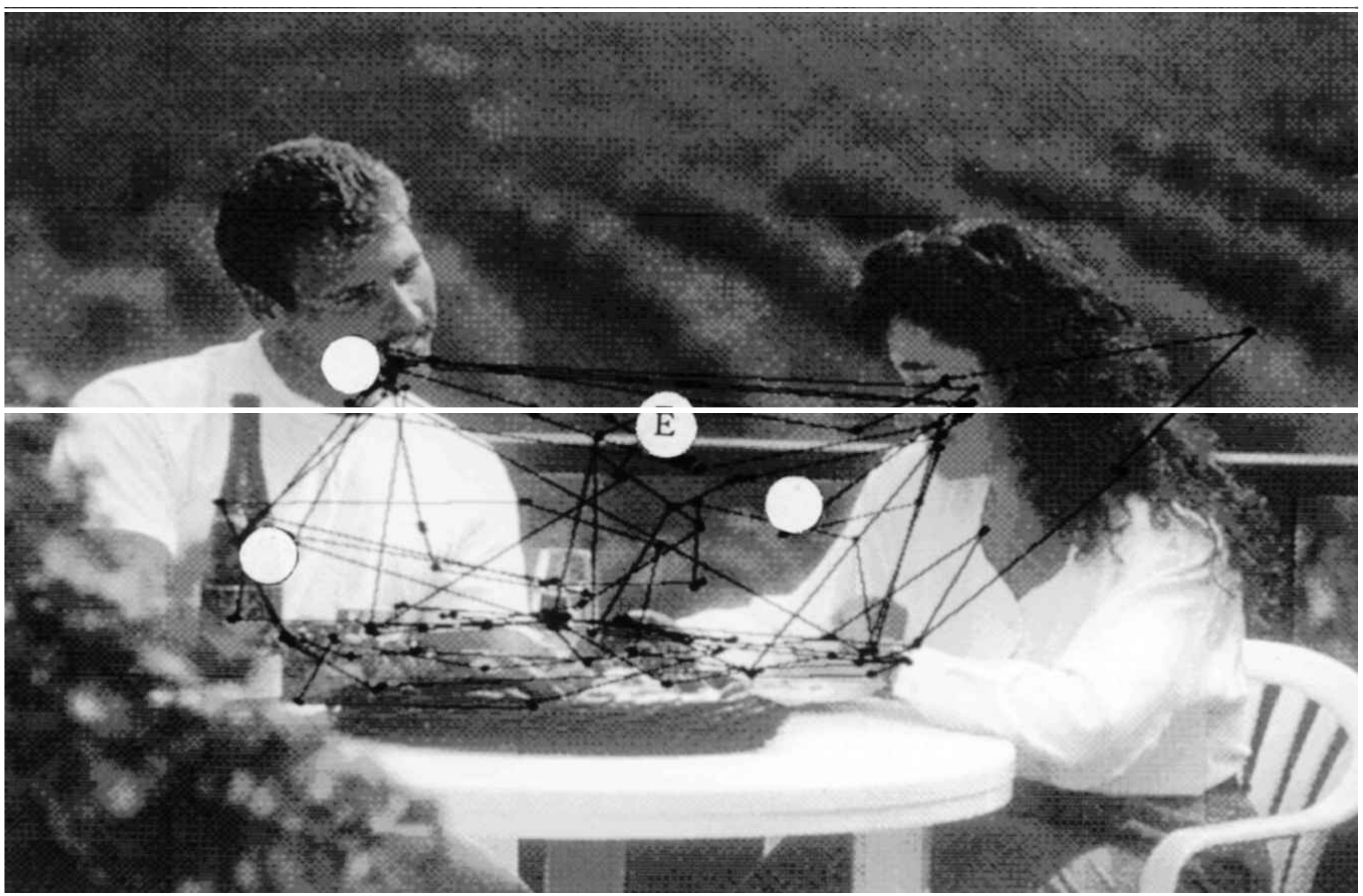
Selection decisions

- multiple localized inputs… one of which is selected for the generation of a supra-threshold peak



Selection decisions

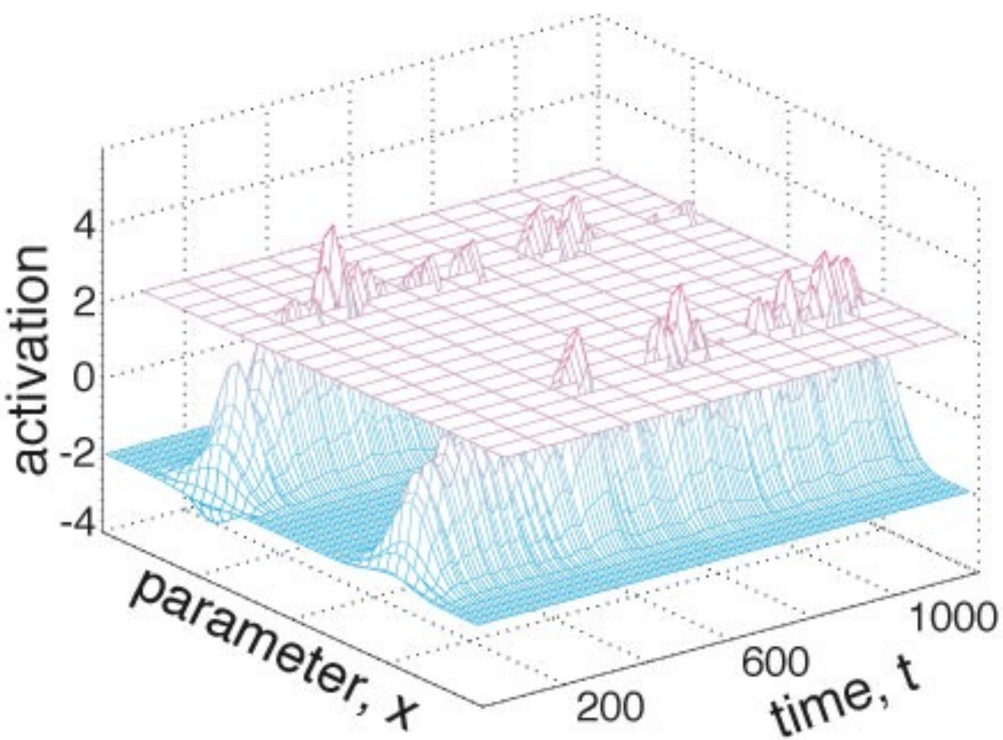
- selecting a new saccadic target location every ~300 ms



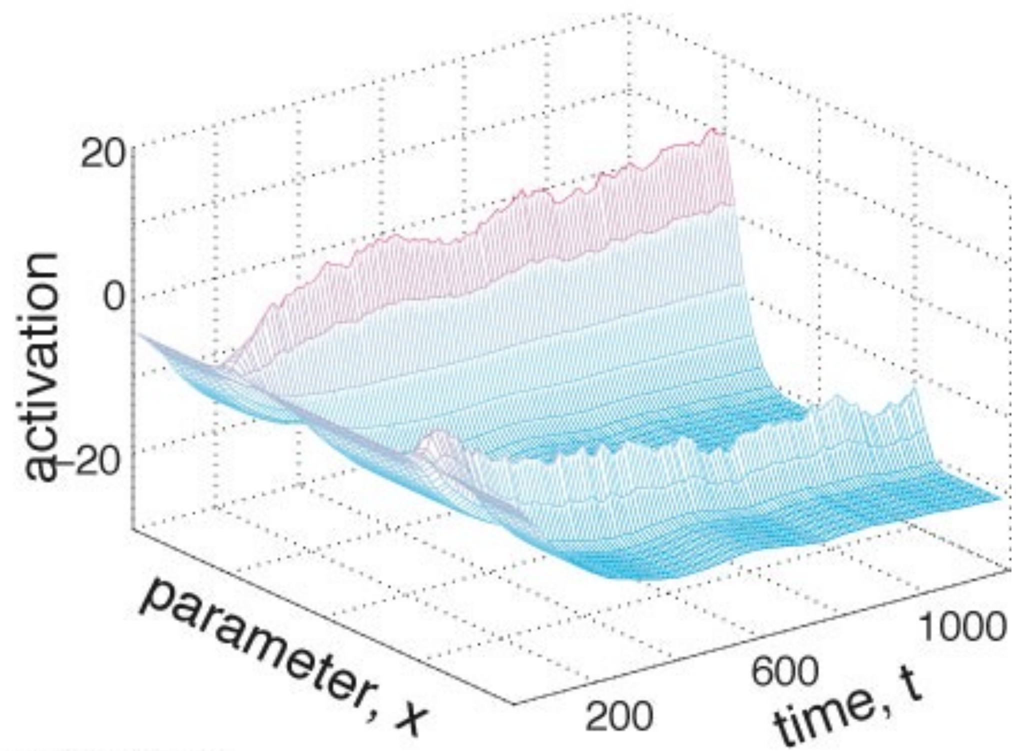
[O'Reagan et al., 2000]

Selection decisions are stable in DFT

"winner takes all"

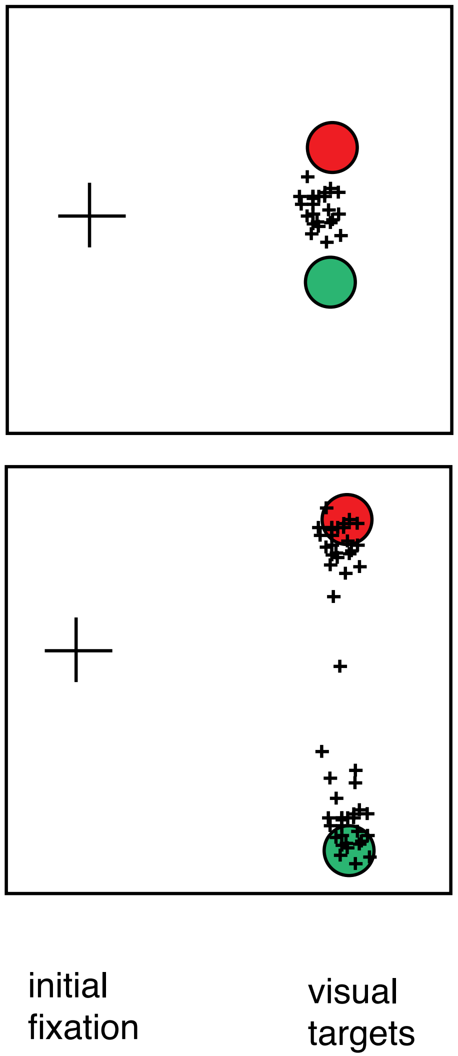


DFT

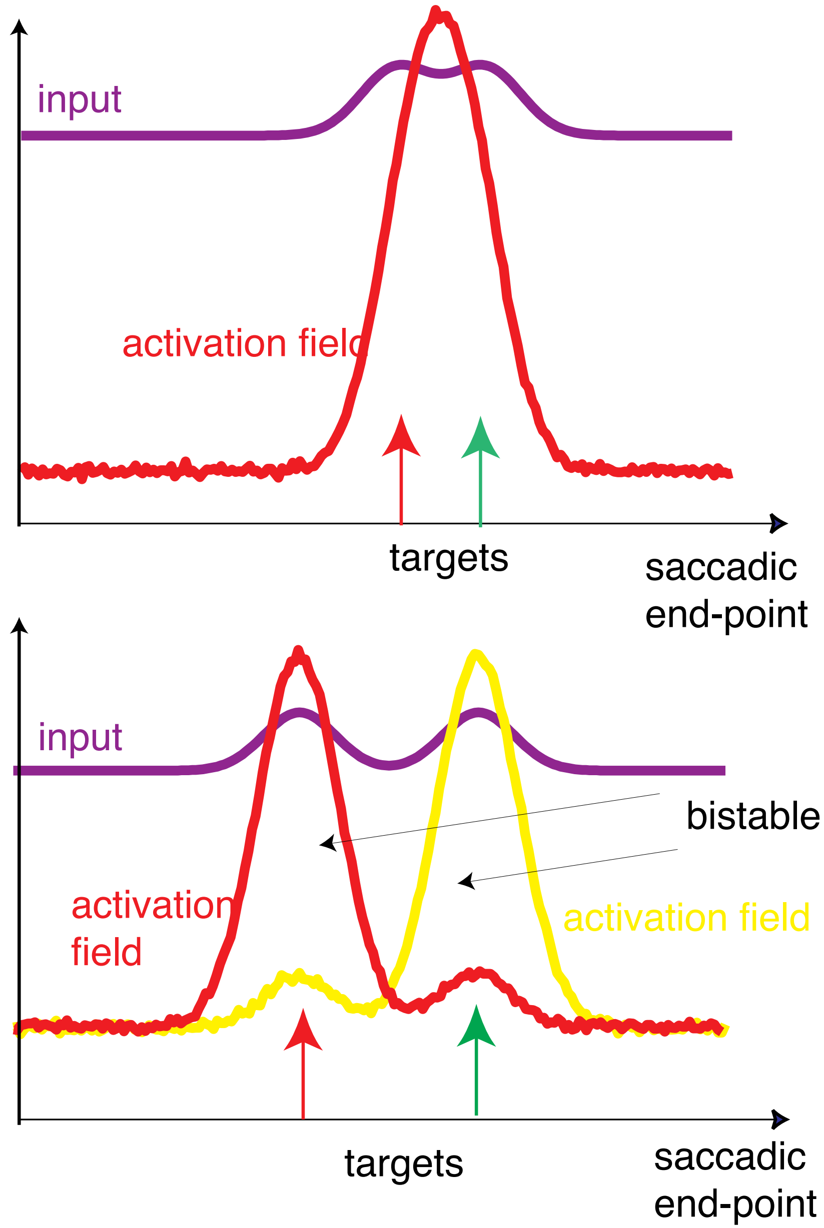


[Wilimzig, Schöner, 2006]

Experimental paradigm

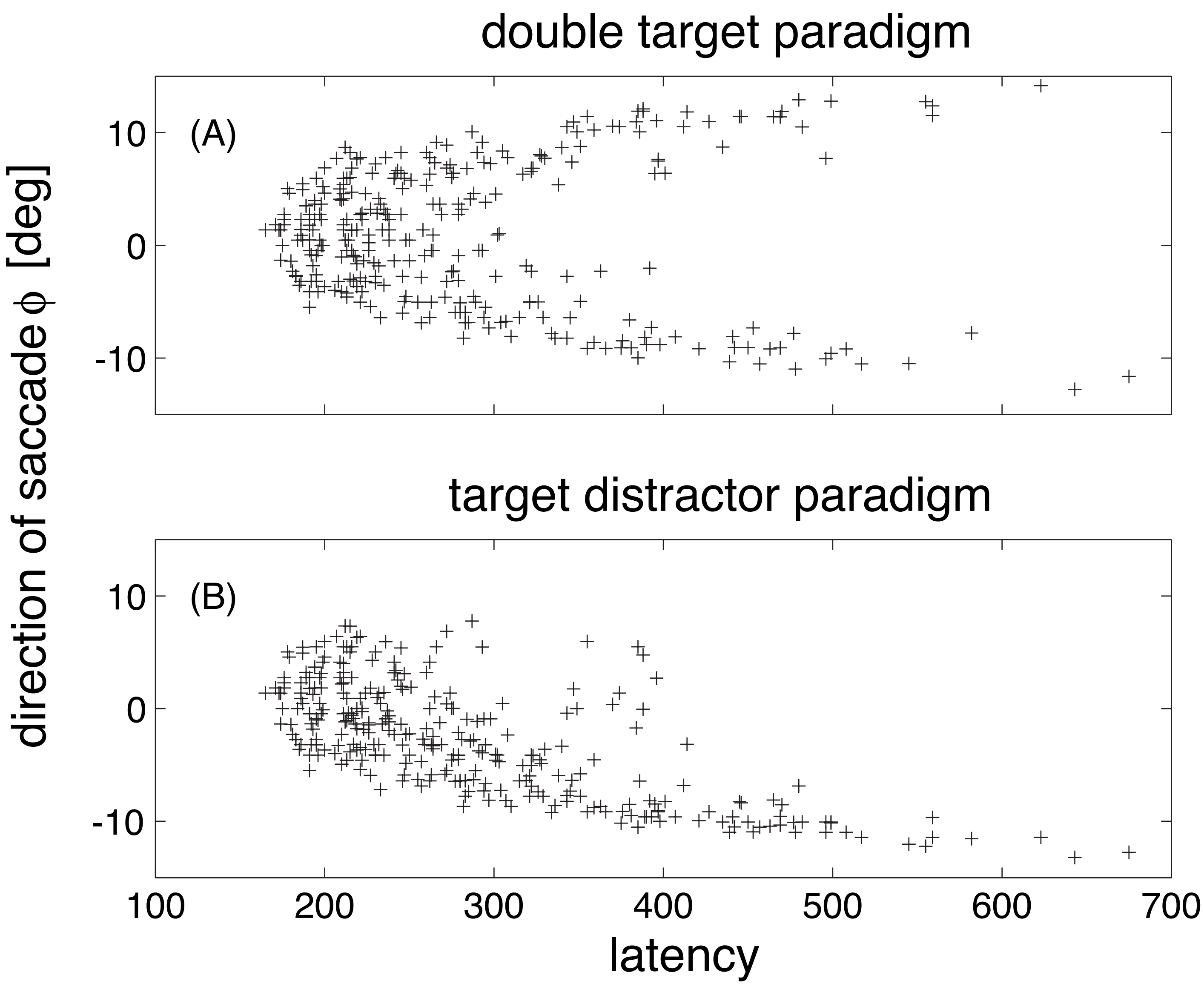


[after: Ottes et al., Vis. Res. 25:825 (85)]



[after Kopecz, Schöner: Biol Cybern 73:49 (95)]

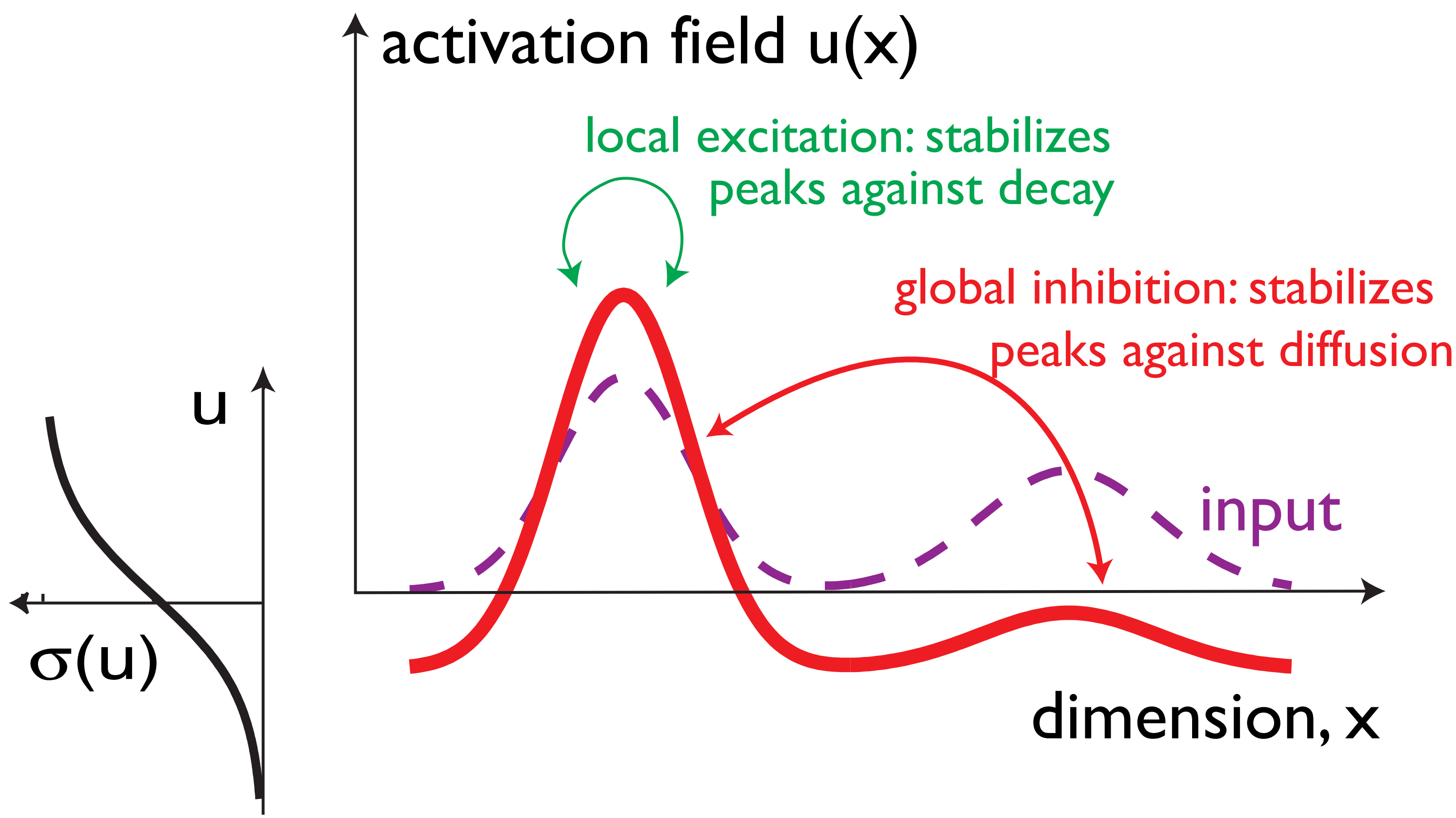
Time course of selection decision



[Wilimzig, Schneider, Schöner, *Neural Networks* 2006]

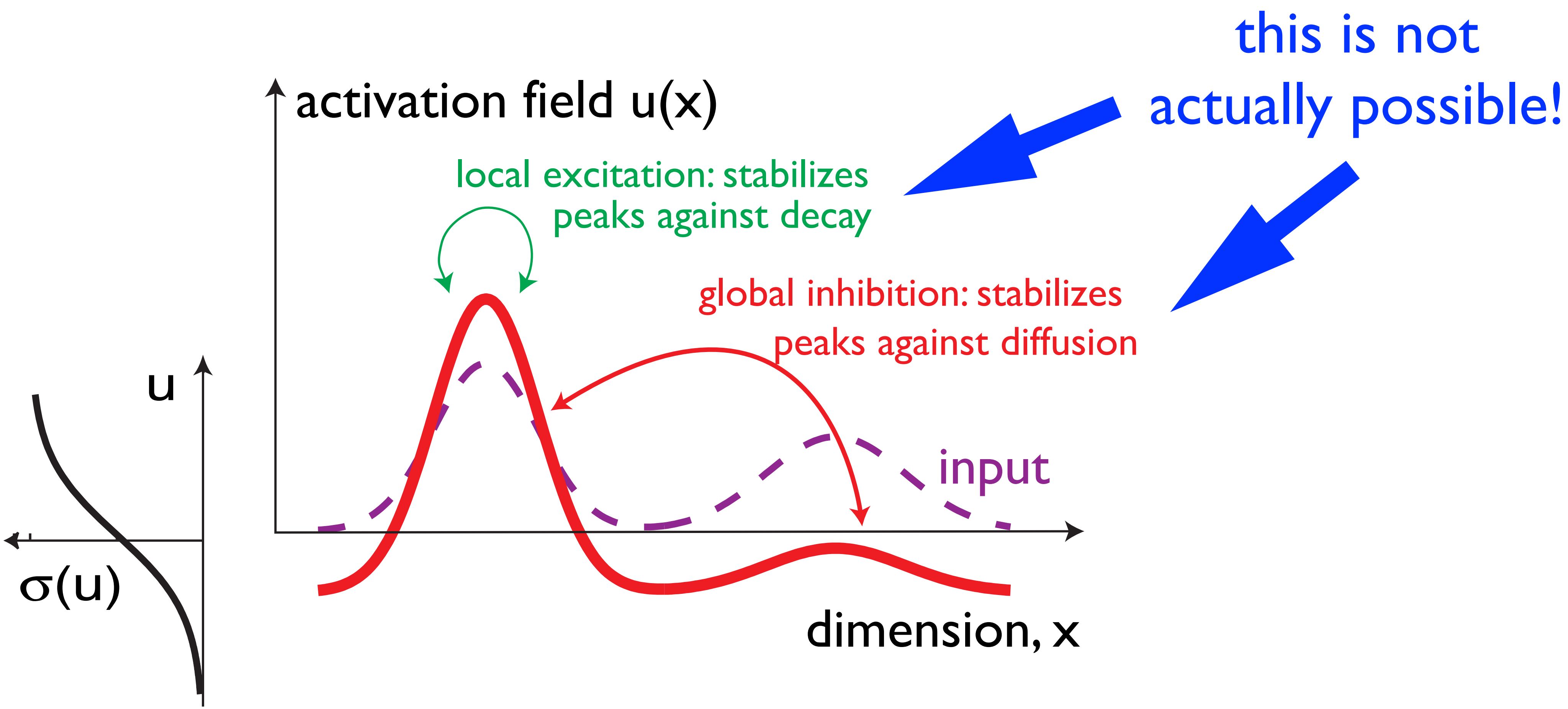
Neural dynamic account?

- so far we assumed that a single population of activation variables has both the excitatory and the inhibitory coupling required to make peaks attractors



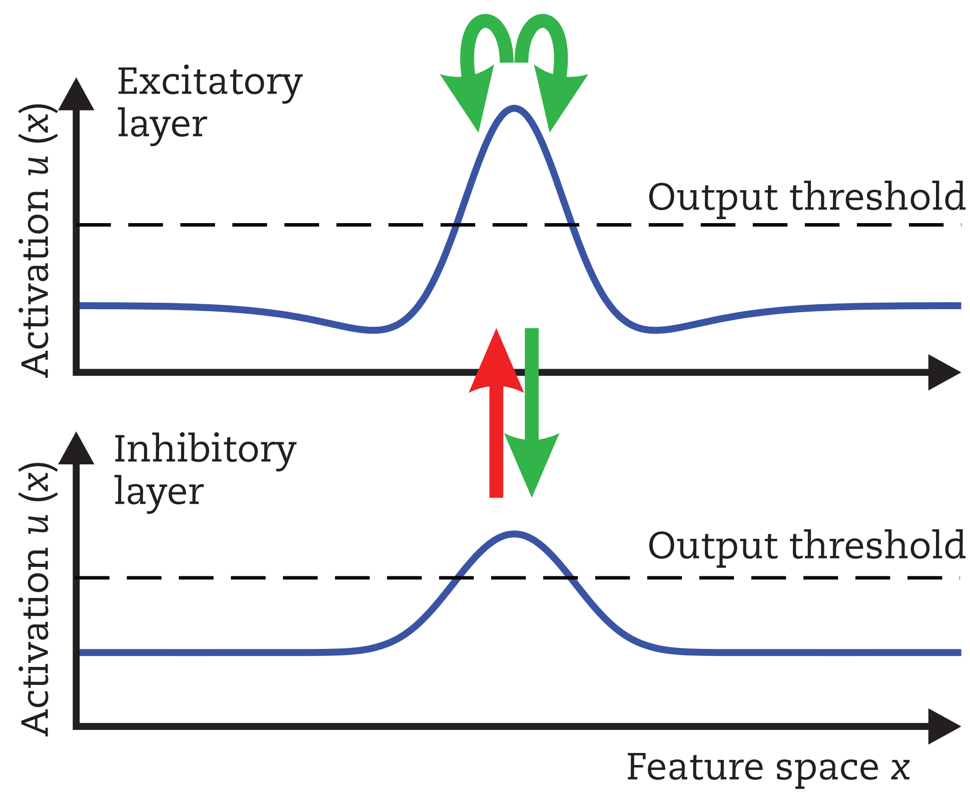
But: Dale's law

- every neuron forms only one type of synapse on the neurons it projects onto: either excitatory or inhibitory



Instead: 2-layer neural fields

- inhibitory coupling is mediated by inhibitory interneurons that
  - are excited by the excitatory layer
  - and in turn inhibit the excitatory layer



[chapter 3 of the book]

Math of 2 layer Amari fields

$$\tau_u \dot{u}(x,t) = -u(x,t) + h_u + s(x,t) + \int k_{uu}(x-x')\sigma(u(x',t))dx' - \int k_{uv}(x-x')\sigma(v(x',t))dx'$$

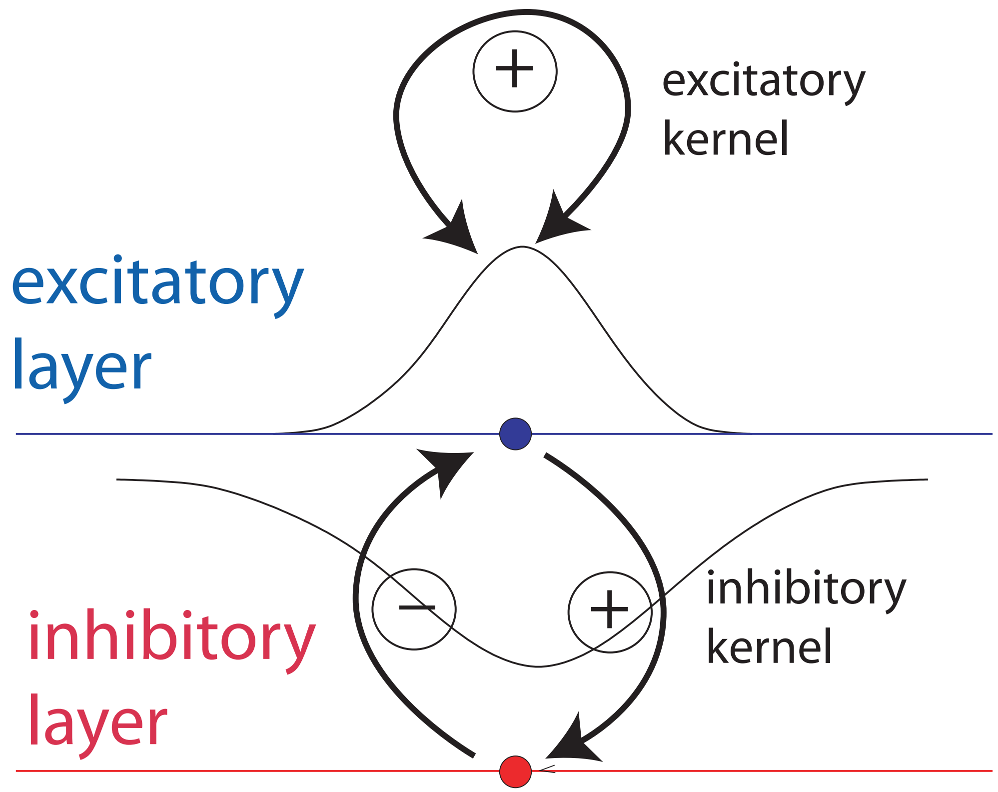
$$\tau_v \dot{v}(x,t) = -v(x,t) + h_v + \int k_{vu}\sigma(u(x',t))dx'$$

with projection kernels

$$k_{ab}(x-x') = c_{ab}\exp\left(-\frac{(x-x')^2}{2\sigma_{ab}^2}\right) \qquad \{a,b\} \in \{u,v\}$$

Time course of selection decision

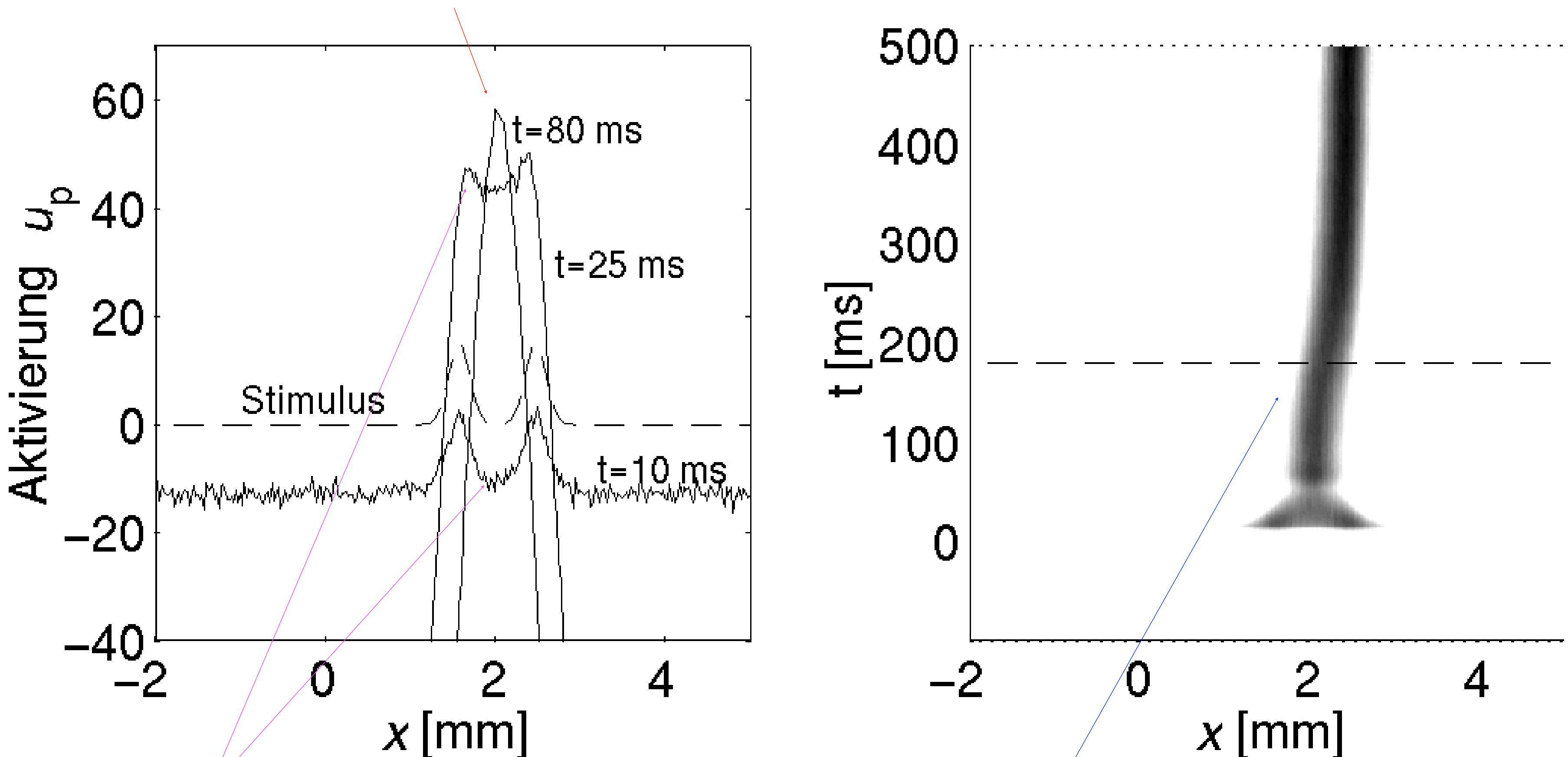
- initially input-dominated
- excitatory interaction arises as once the excitatory field goes through threshold
- inhibition arises only after that has happened… when inhibitory field exceeds threshold => begin to see inhibitory interaction



[Wilimzig, Schneider, Schöner, *Neural Networks* 2006]

Time course of selection decision

intermediate: dominated by excitatory interaction

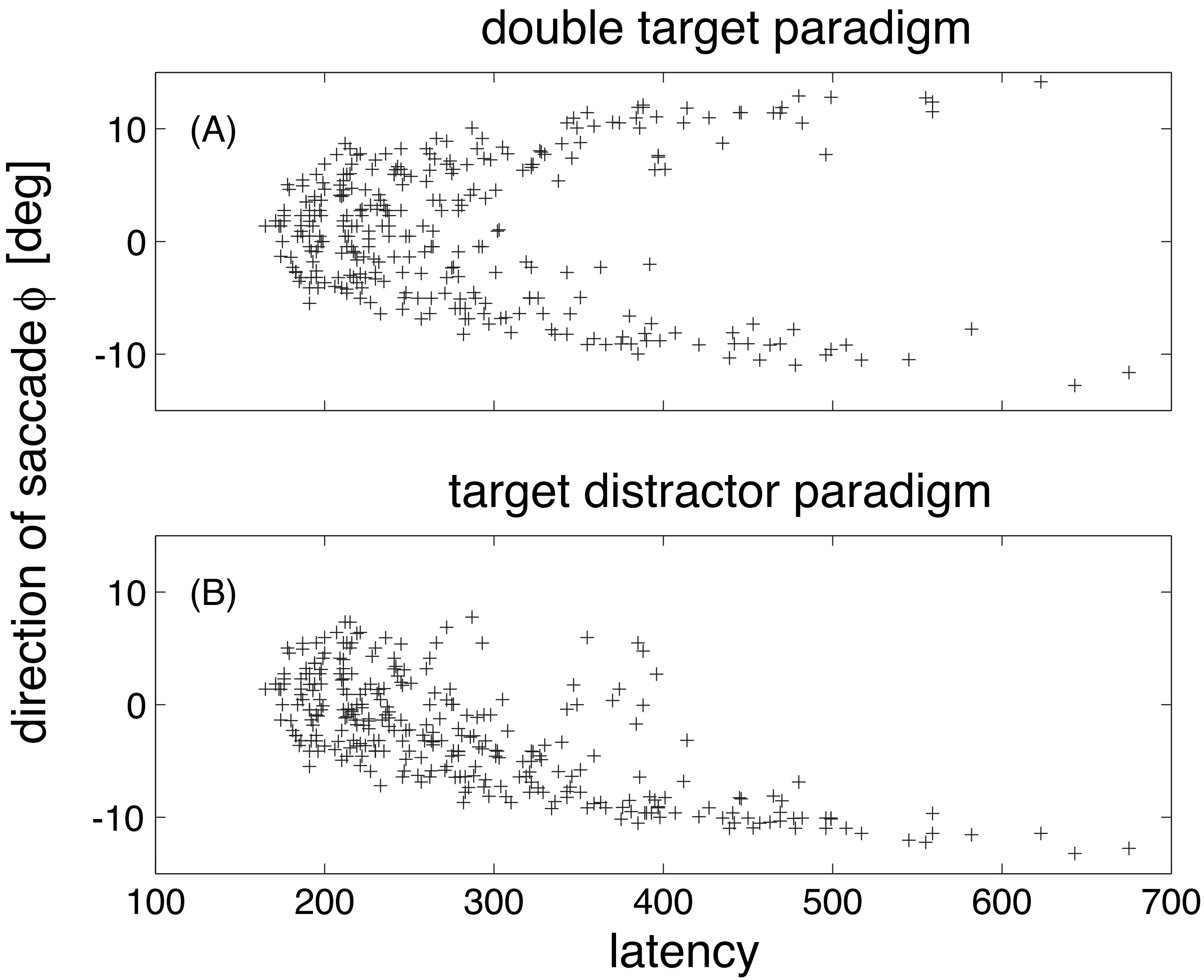


early: input driven

late: inhibitory interaction drives selection

[Wilimzig, Schneider, Schöner, *Neural Networks* 2006]

=> early fusion, late selection



[Wilimzig, Schneider, Schöner, *Neural Networks* 2006]

(2 layer fields afford oscillations

- … will be important for movement generation
- and for sequence generation…)

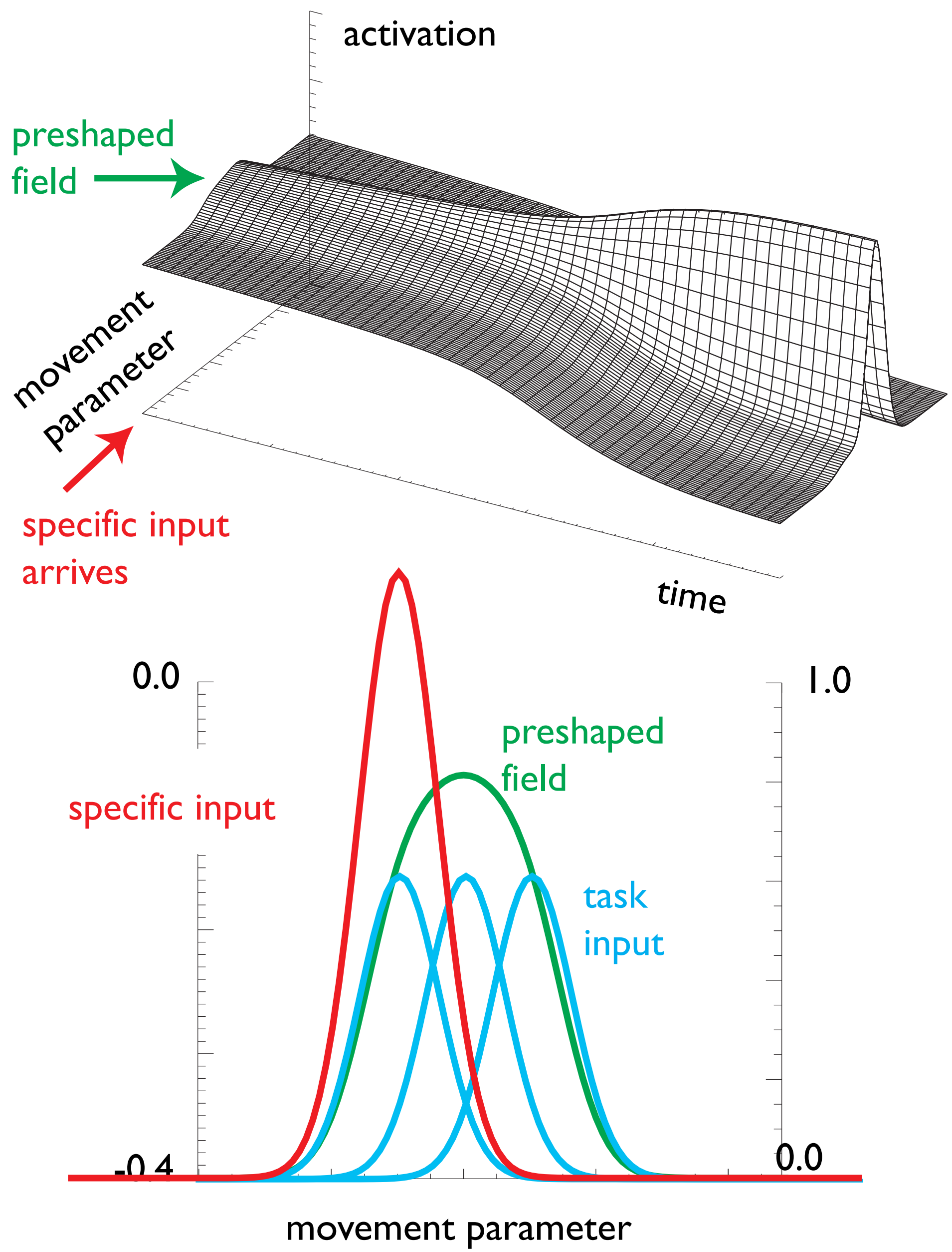
Selection decisions in the laboratory

- most experiments in cognition entail selection decisions!
- in most of these paradigms an imperative signal uniquely specifies the "correct" response
- what is varied is e.g.
  - the nature of the imperative stimulus
  - the task set
  - experience with the task

Task set

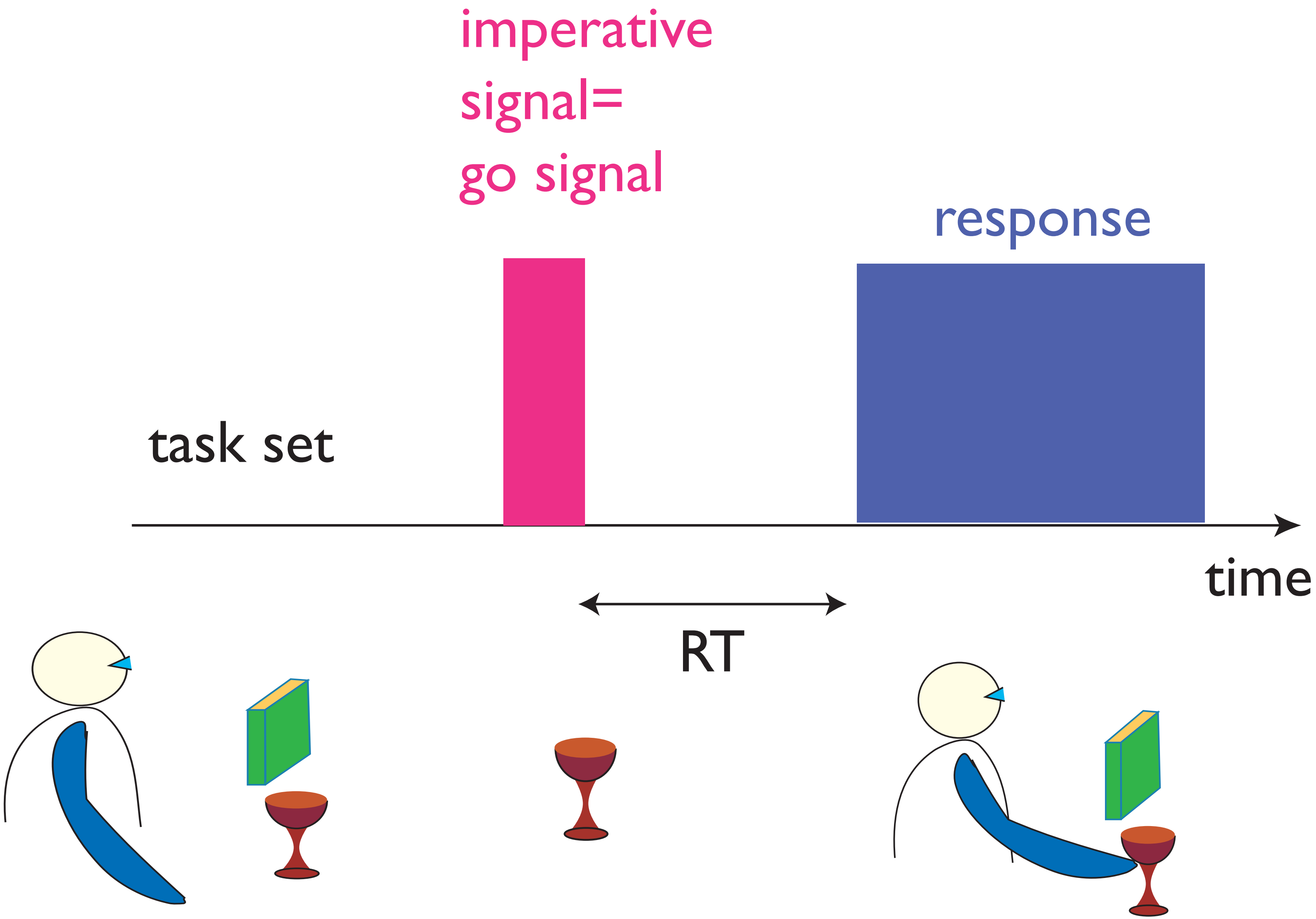
- examples: number or probability of choices, perceptual quality of imperative stimulus, difficulty of the match between imperative stimulus and learned category …
- the task set is known to the participant prior to the presentation of the imperative signal
  - by instruction
  - by perceptual layout
  - by learning
- => task set "preshapes" the underlying representations (pre=before the selection decision)

Task set as “preshape”

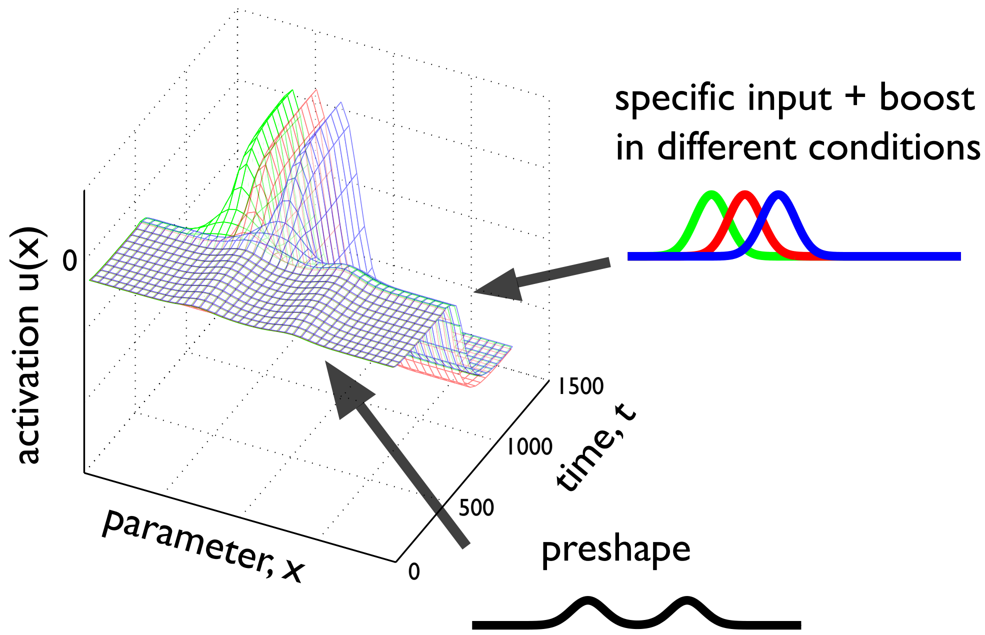


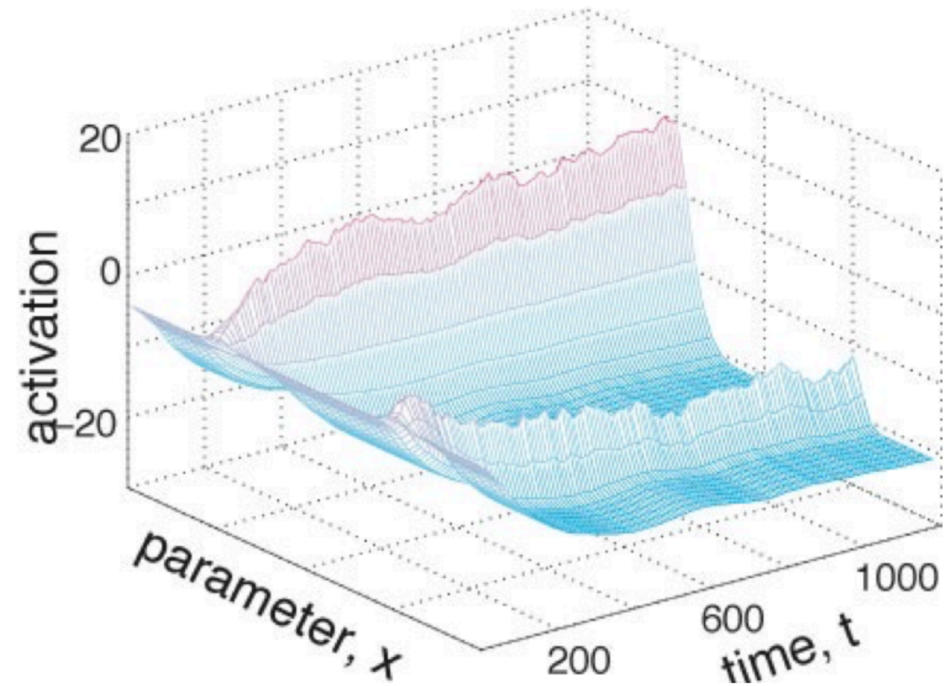
[Erlhagen, Schöner, *Psych Rev* 2002]

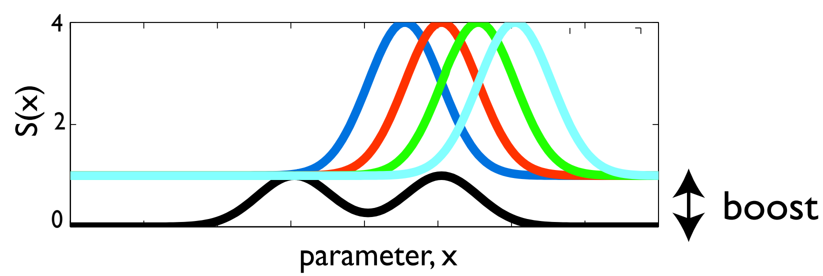
Reaction time (RT) paradigm

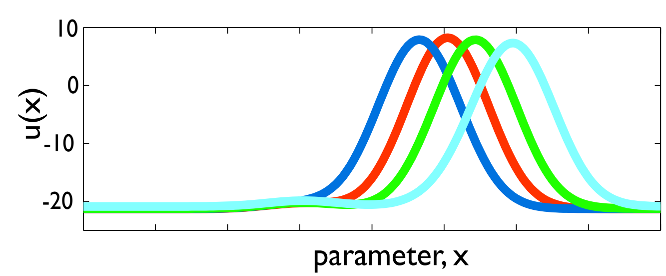


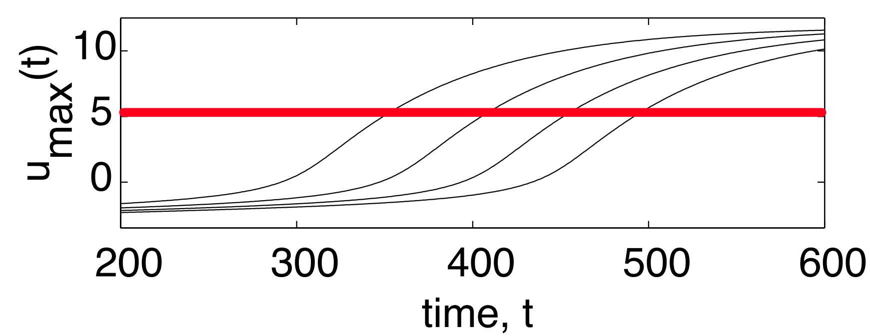
Reaction time task in DFT







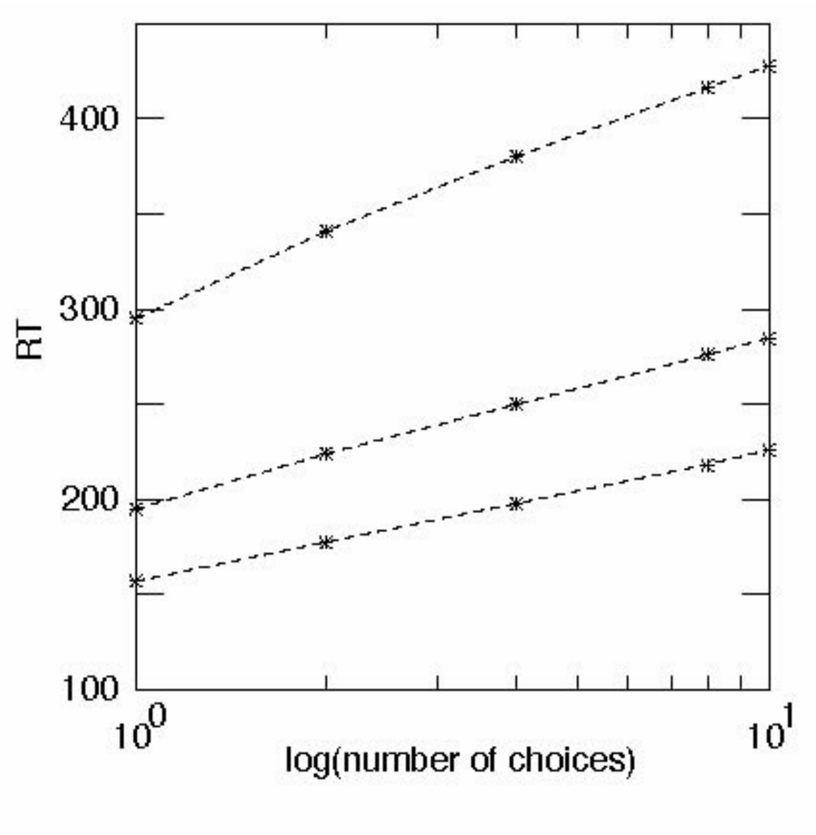


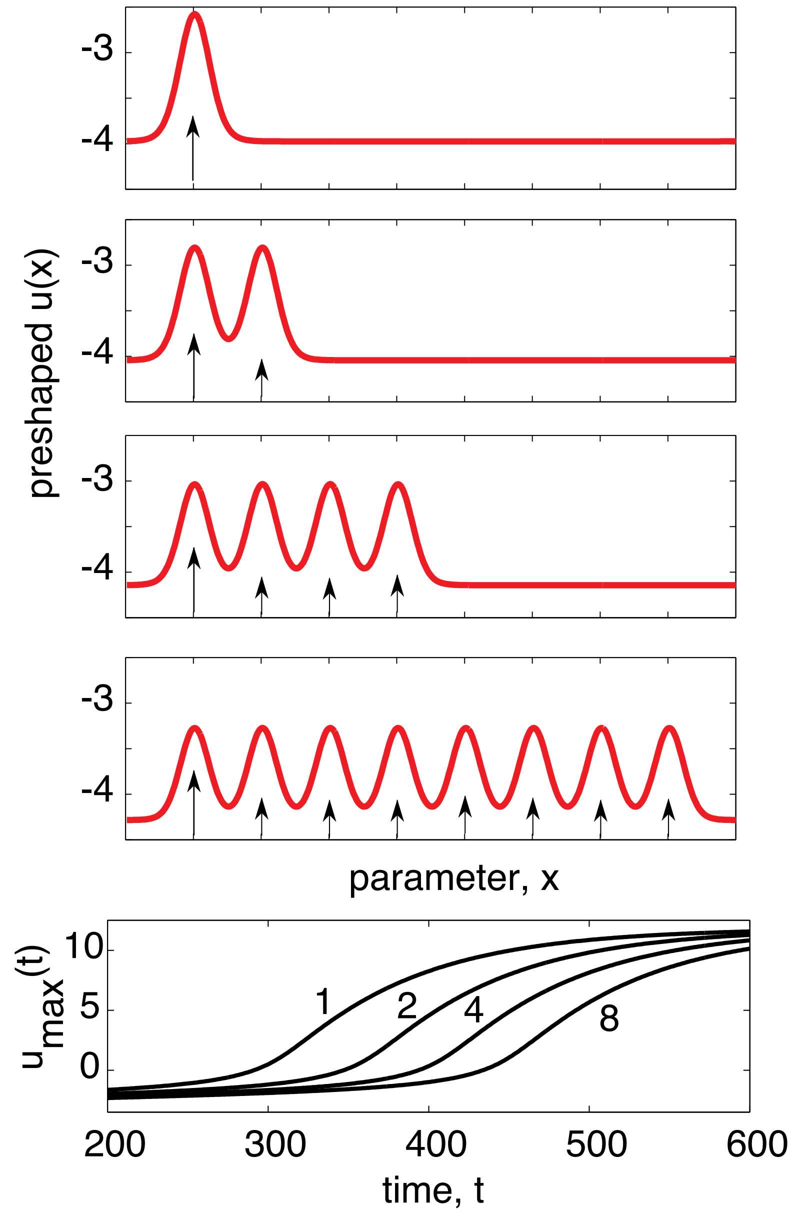


[Wilimzig, Schöner, 2006]

Hick's law

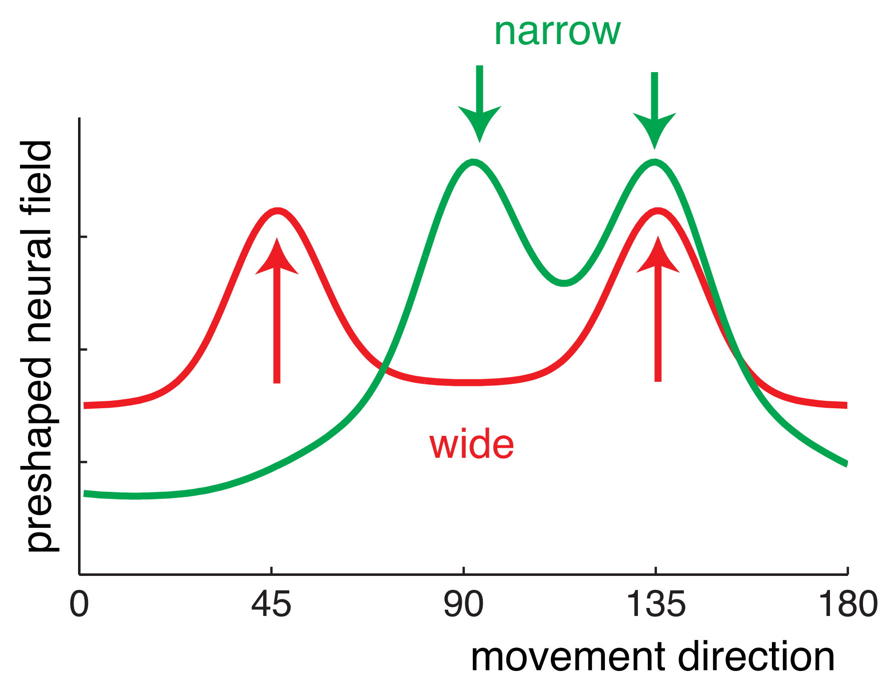
- RT increases with the number of choices



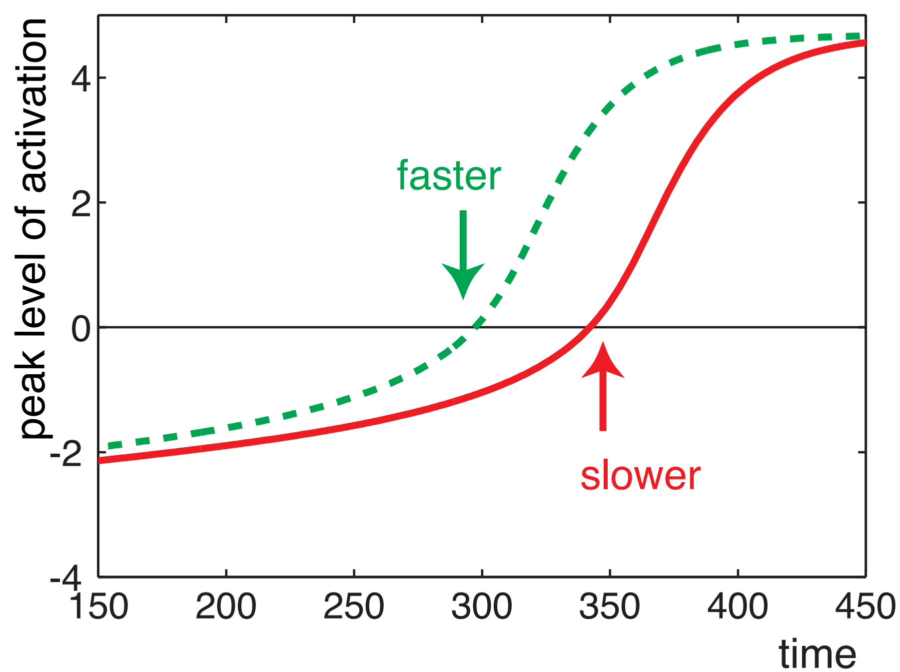


[Erlhagen, Schöner, *Psych Rev* 2002]

Metric effect

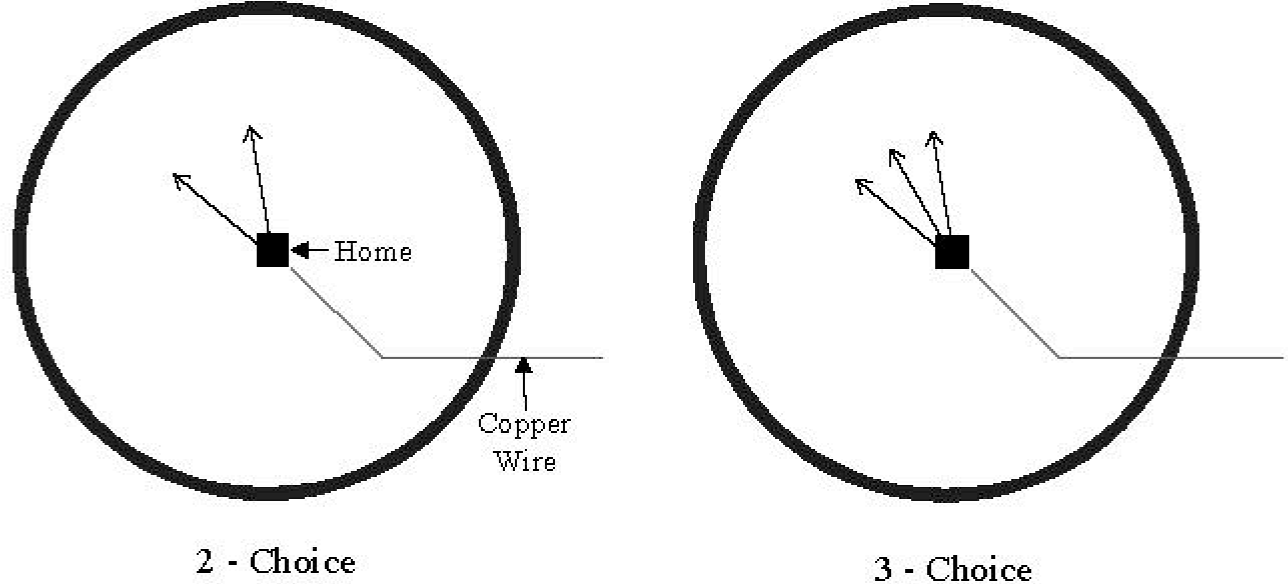


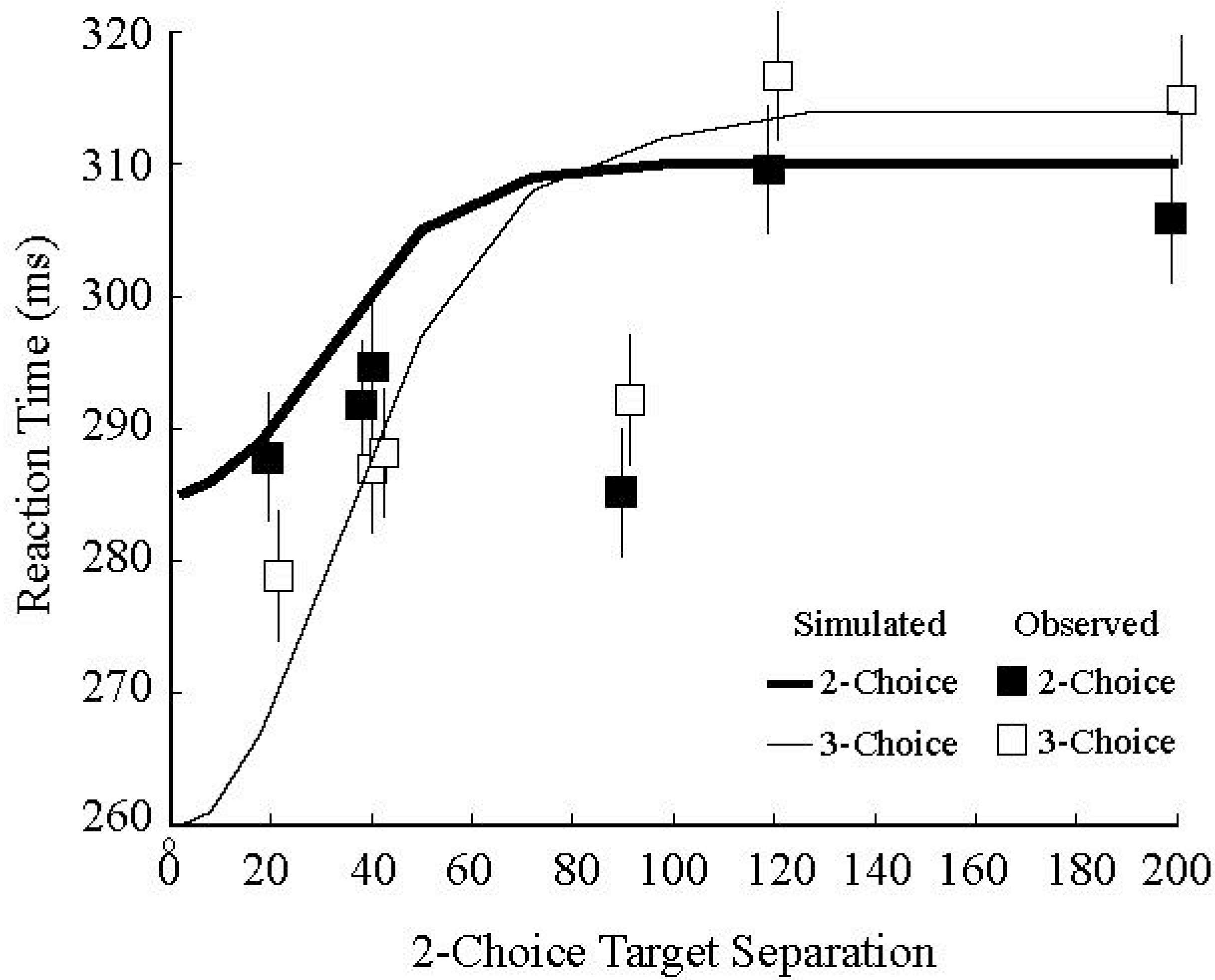
- predict faster response times for metrically close than for metrically far choices



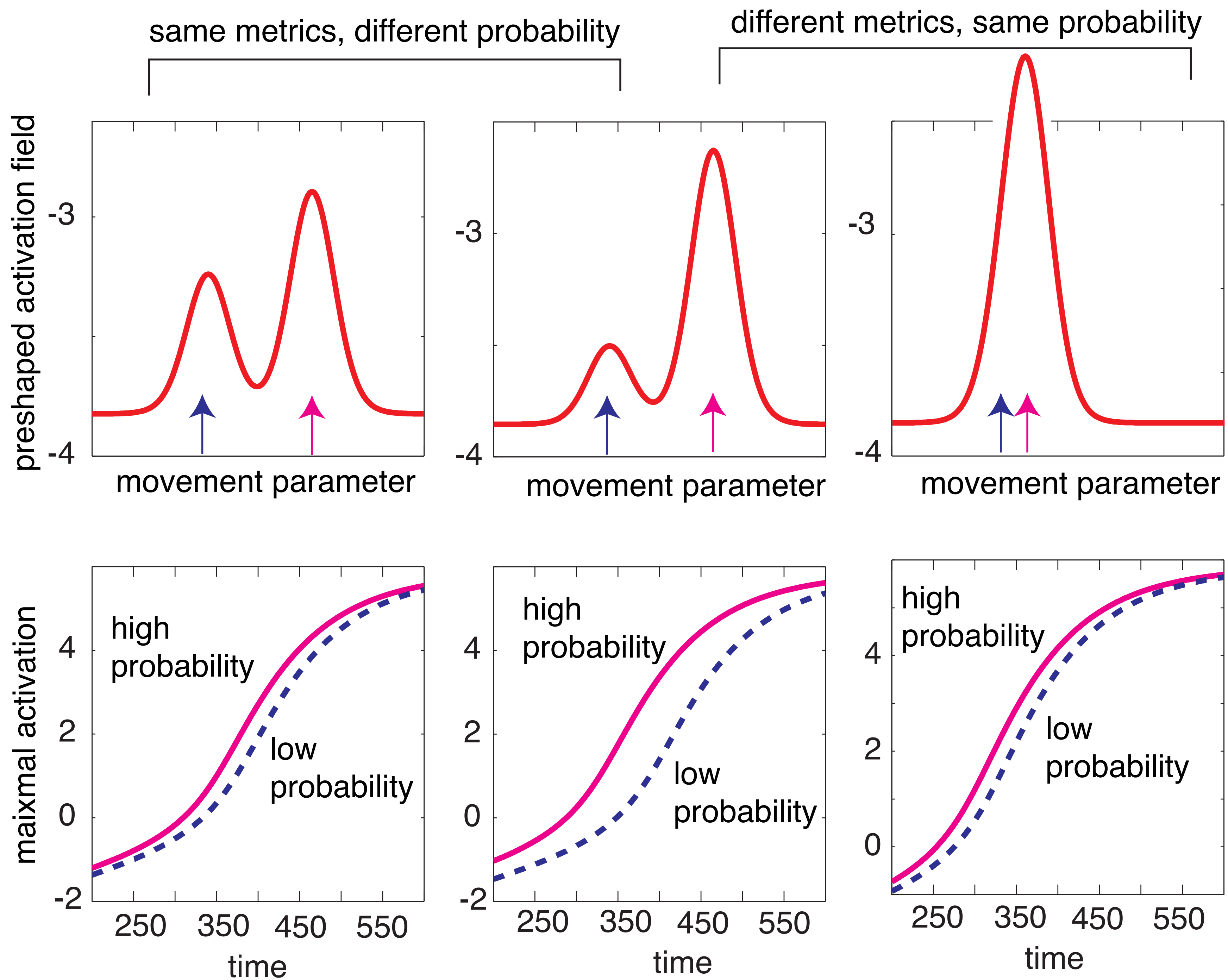
[Erlhagen, Schöner, *Psych Rev* 2002]

Metric effect: experiment

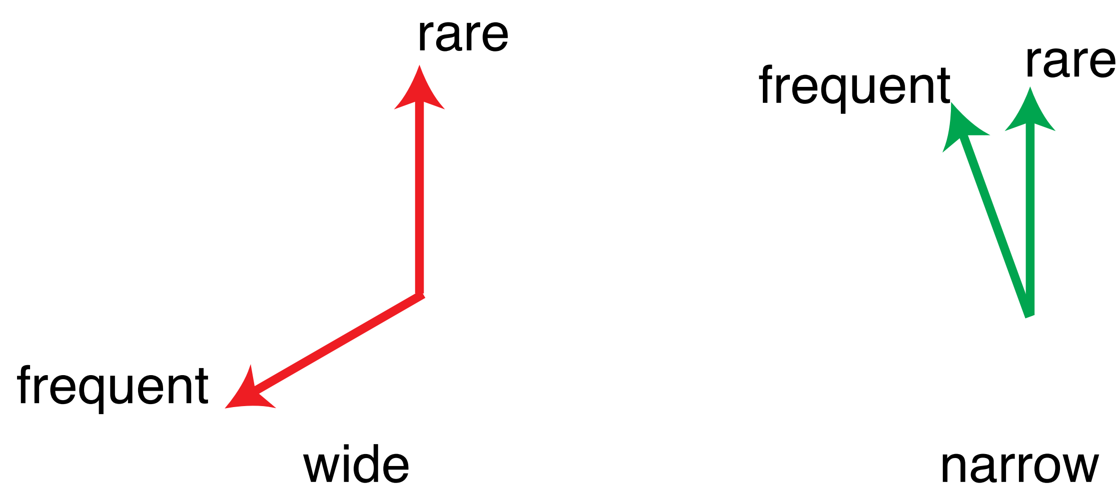


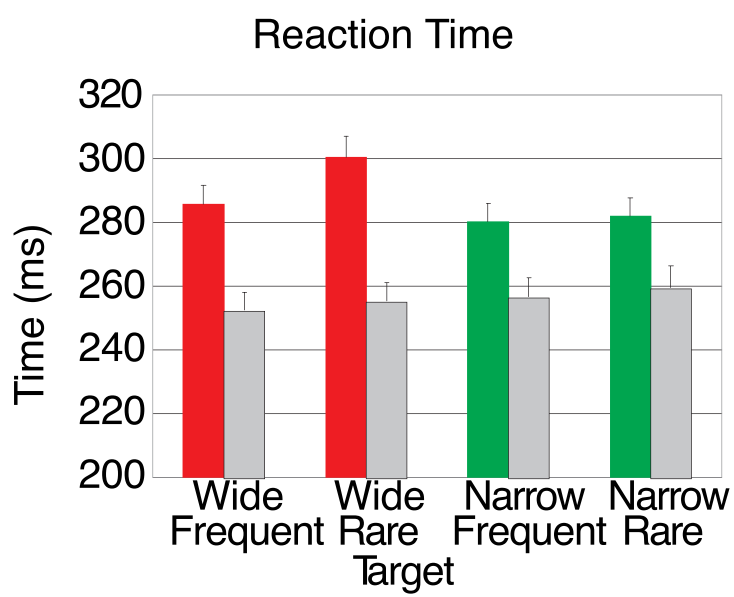


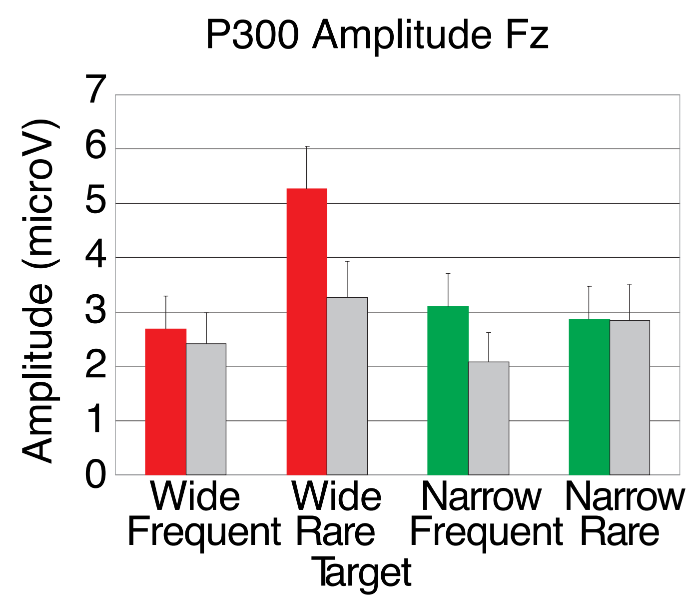
[McDowell, Jeka, Schöner]



[from Erlhagen, Schöner: Psych. Rev. 2002]



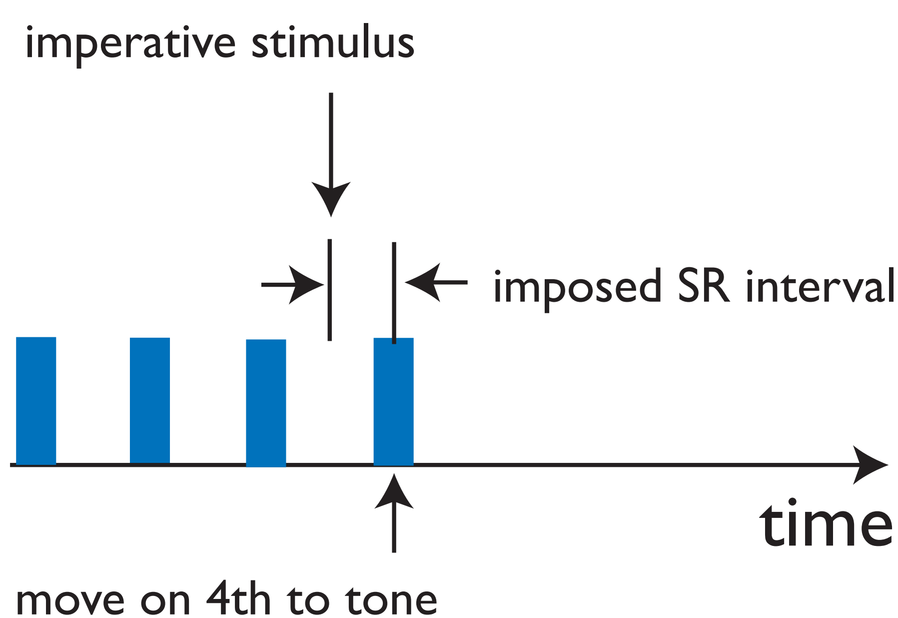




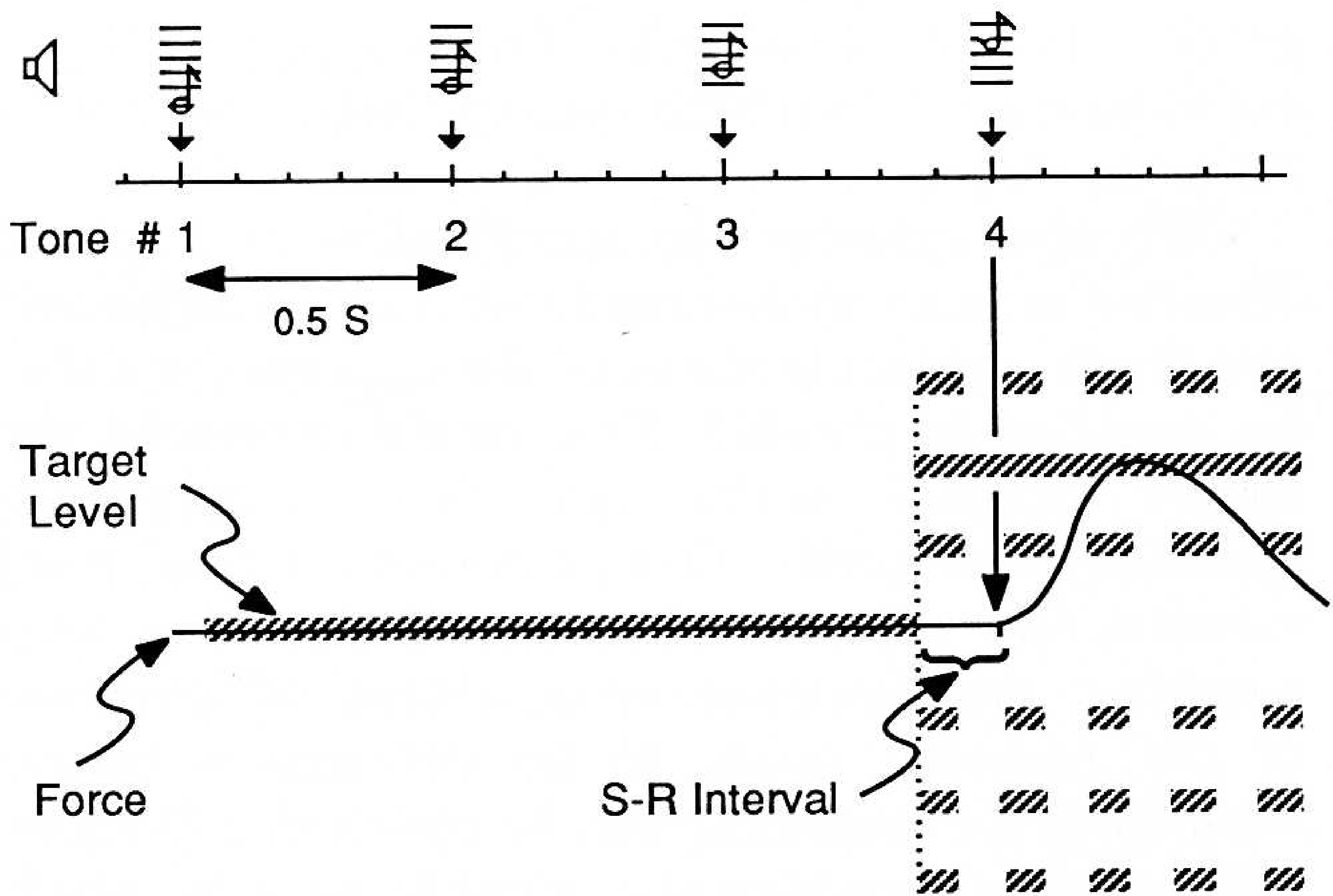
[from McDowell, Jeka, Schöner, Hatfield, 2002]

Behavioral evidence for graded/time-continuous evolution of selection decisions

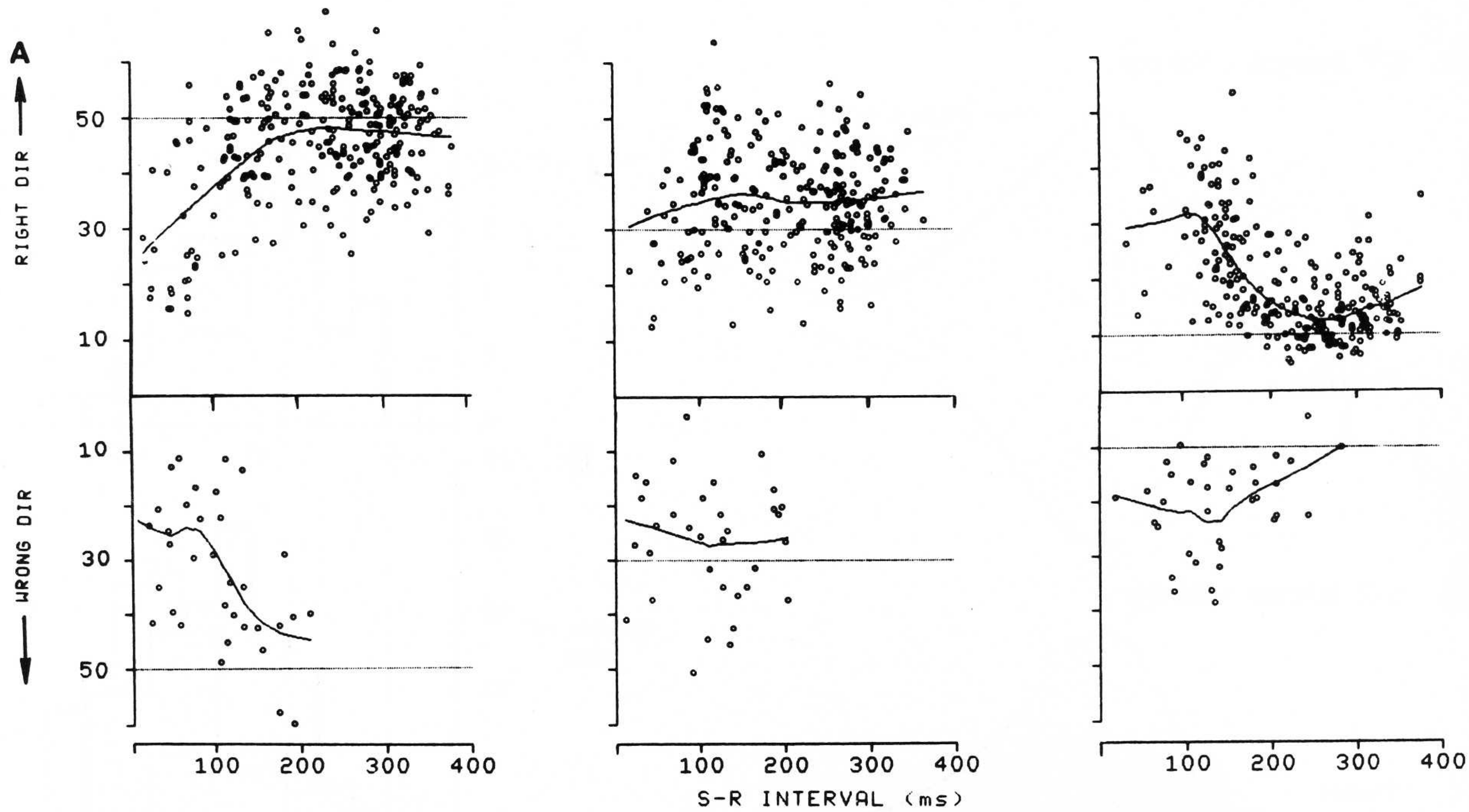
timed movement
initiation paradigm



[Ghez and colleagues, 1988 to 1990's]

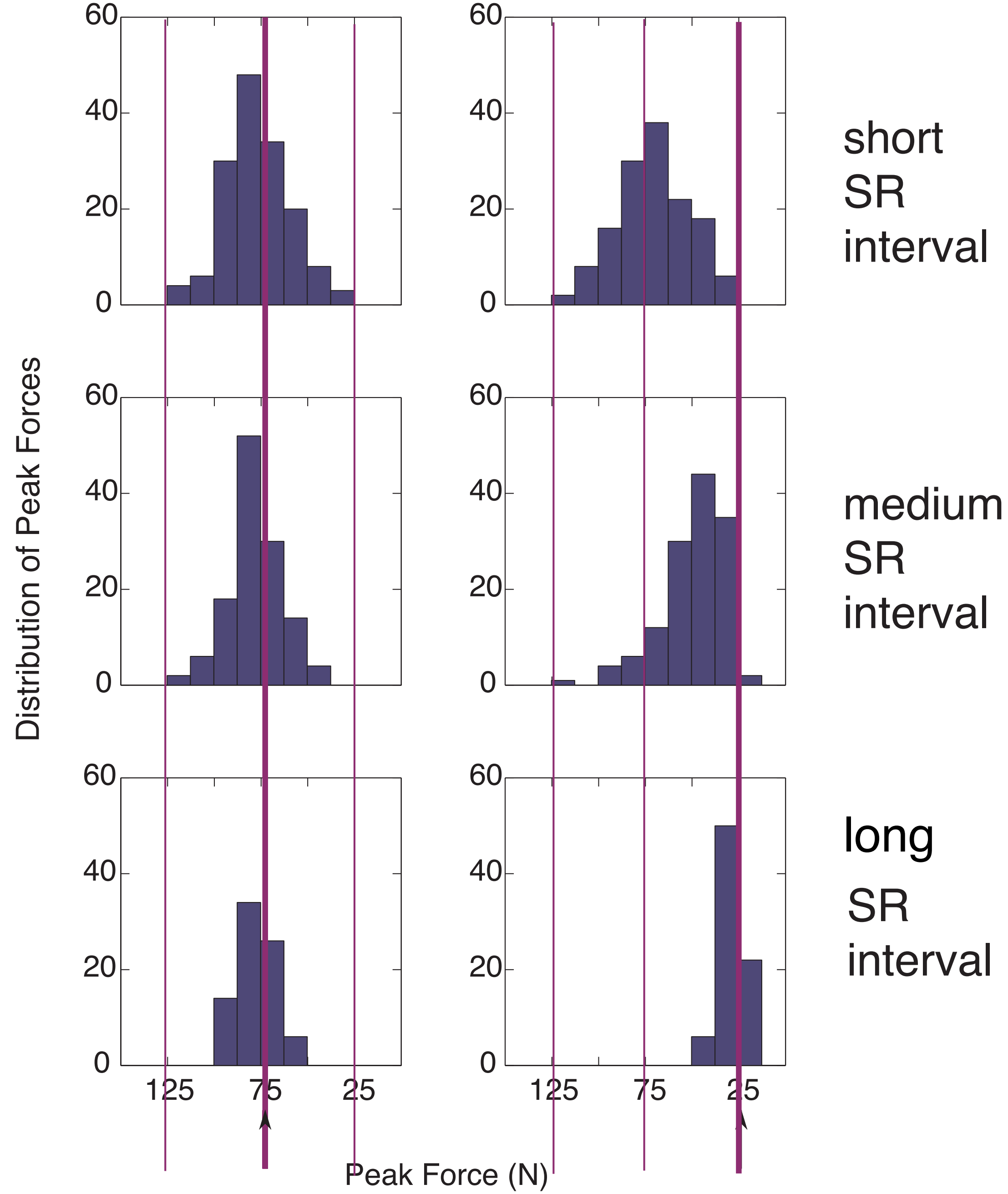


[Favilla et al. 1989]

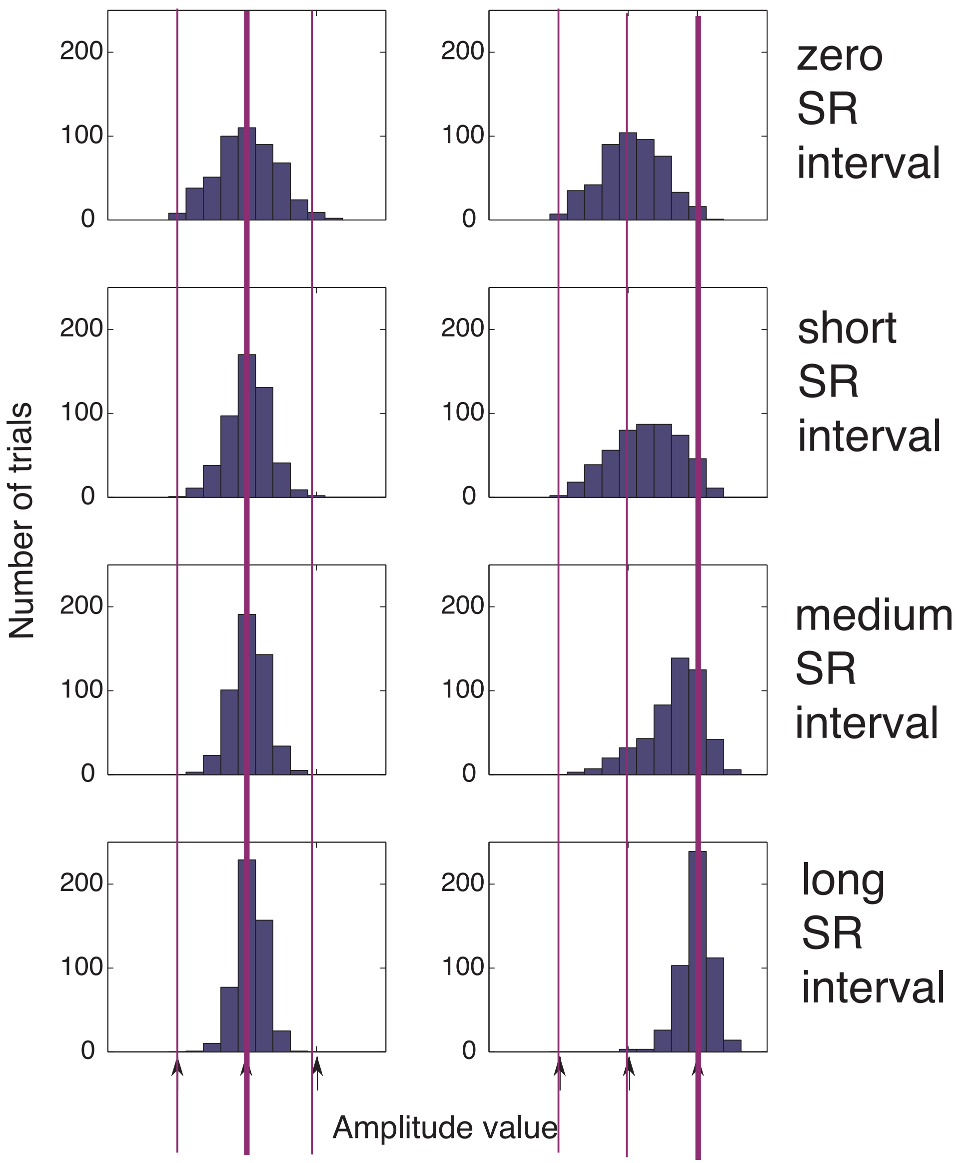


[Favilla et al. 1989]

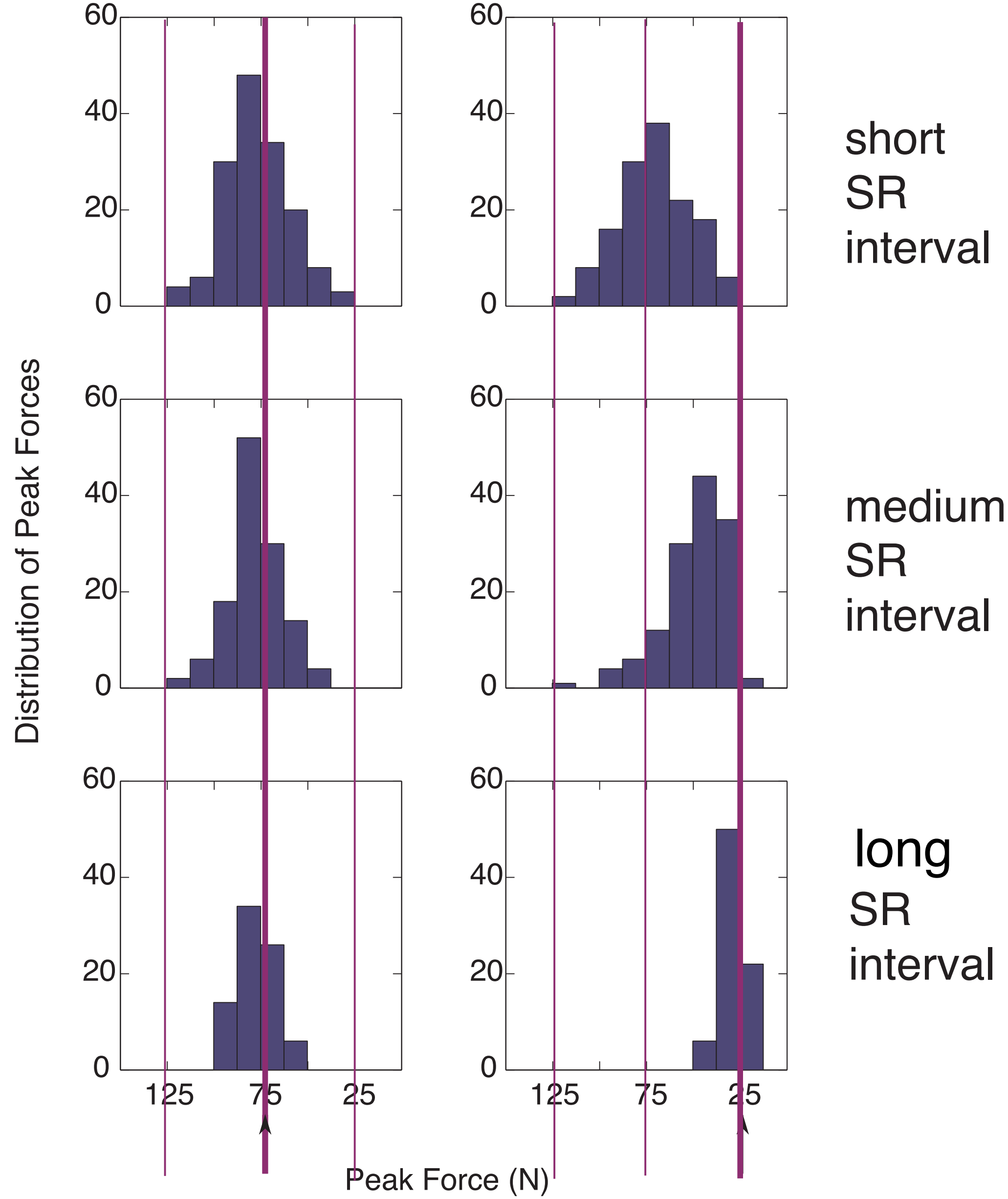
Experimental results of Henig et al



theoretical account for Henig et al.

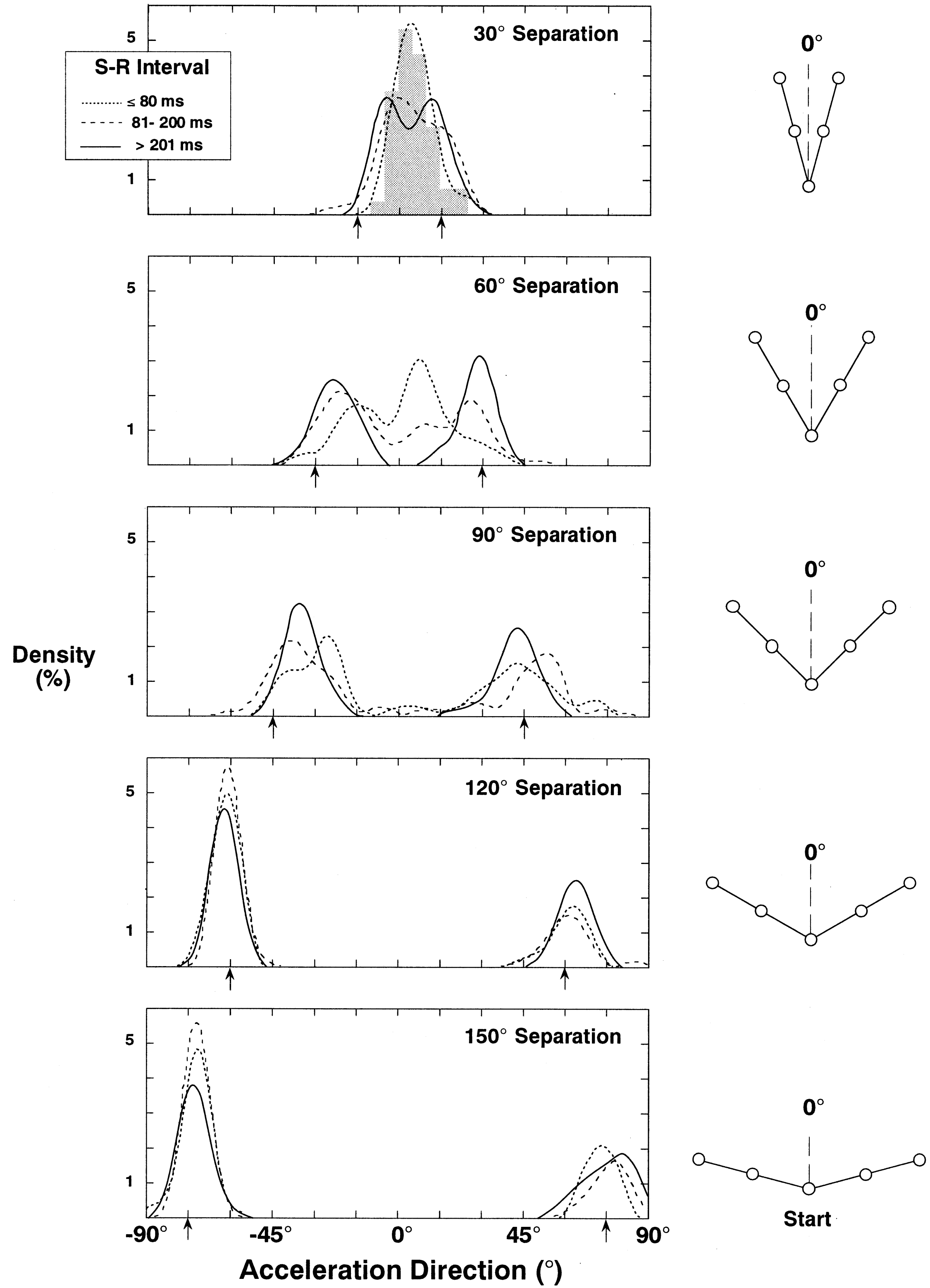


Experimental results of Henig et al



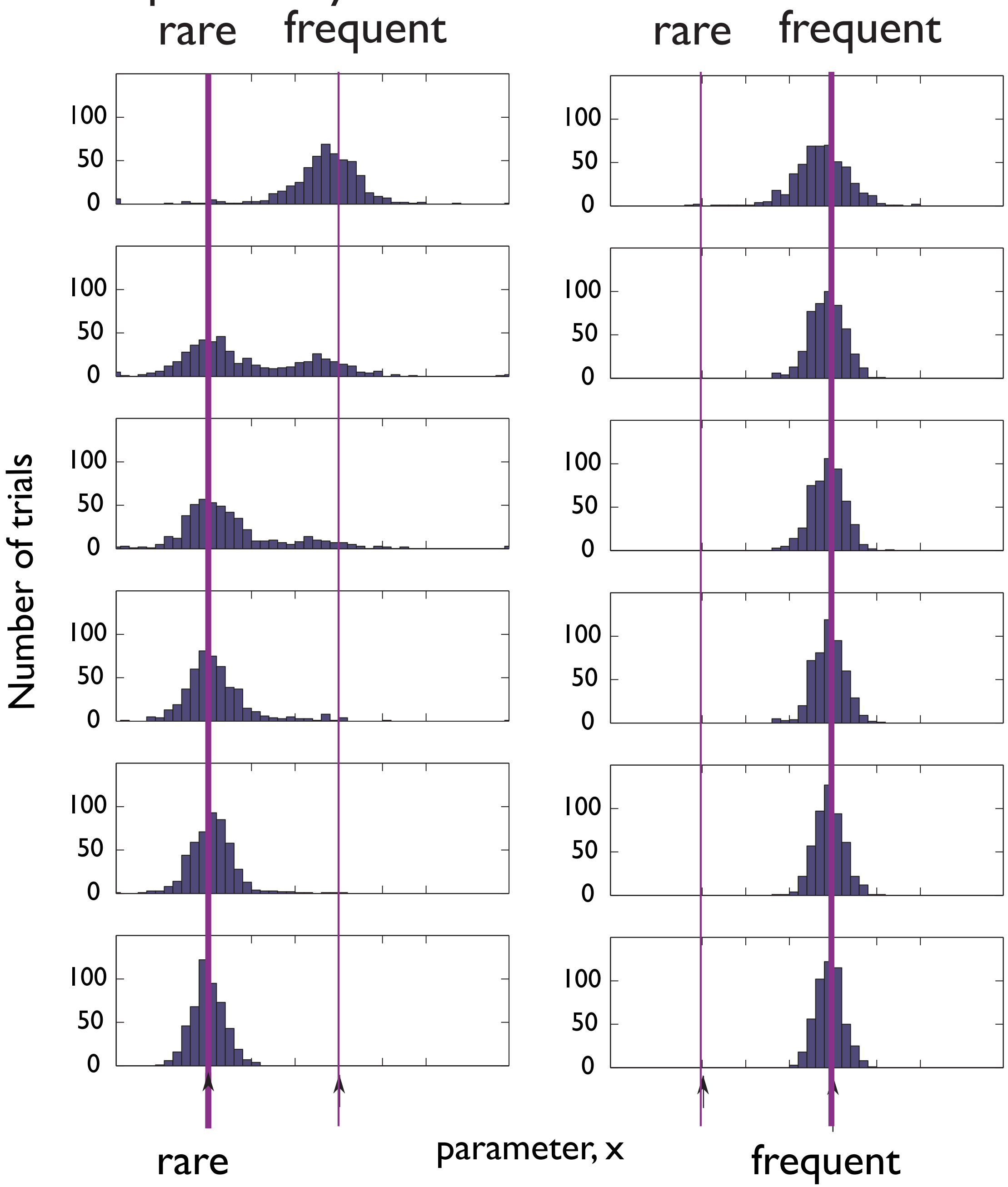
[Erlhagen, Schöner. 2002, Psychological Review 109, 545–572 (2002)]

- infer width of preshape peaks in field



[Ghez et al 1997]

probability in timed movement initiation

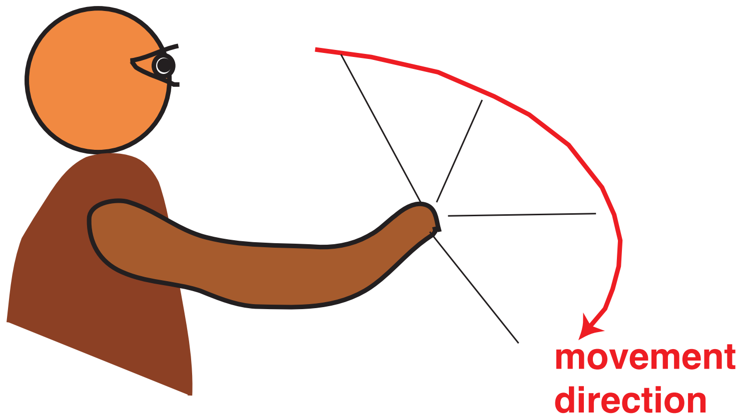


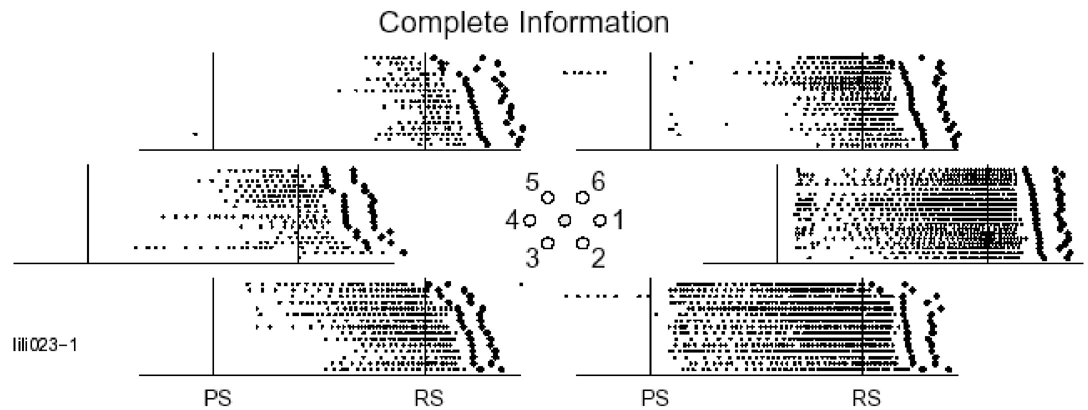
short SR interval:
observe preshape

long SR interval:
observe stimulus-defined
movement plan

Ghez et al, 1997

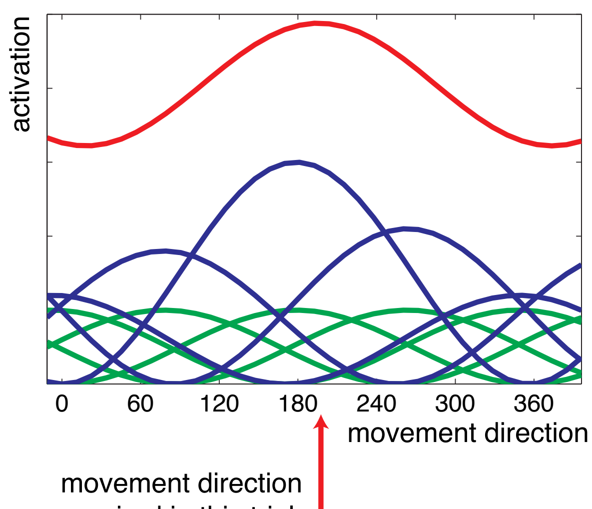
Neural evidence for preshape



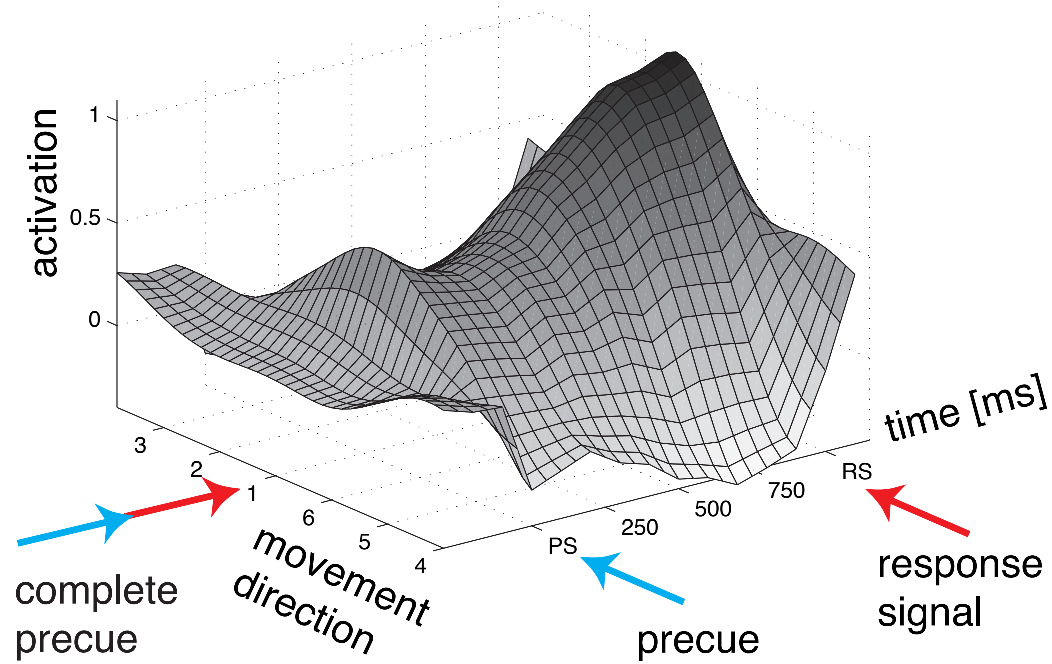


Distribution of population activation =

$\sum_{\text{neurons}}$ tuning curve * current firing rate

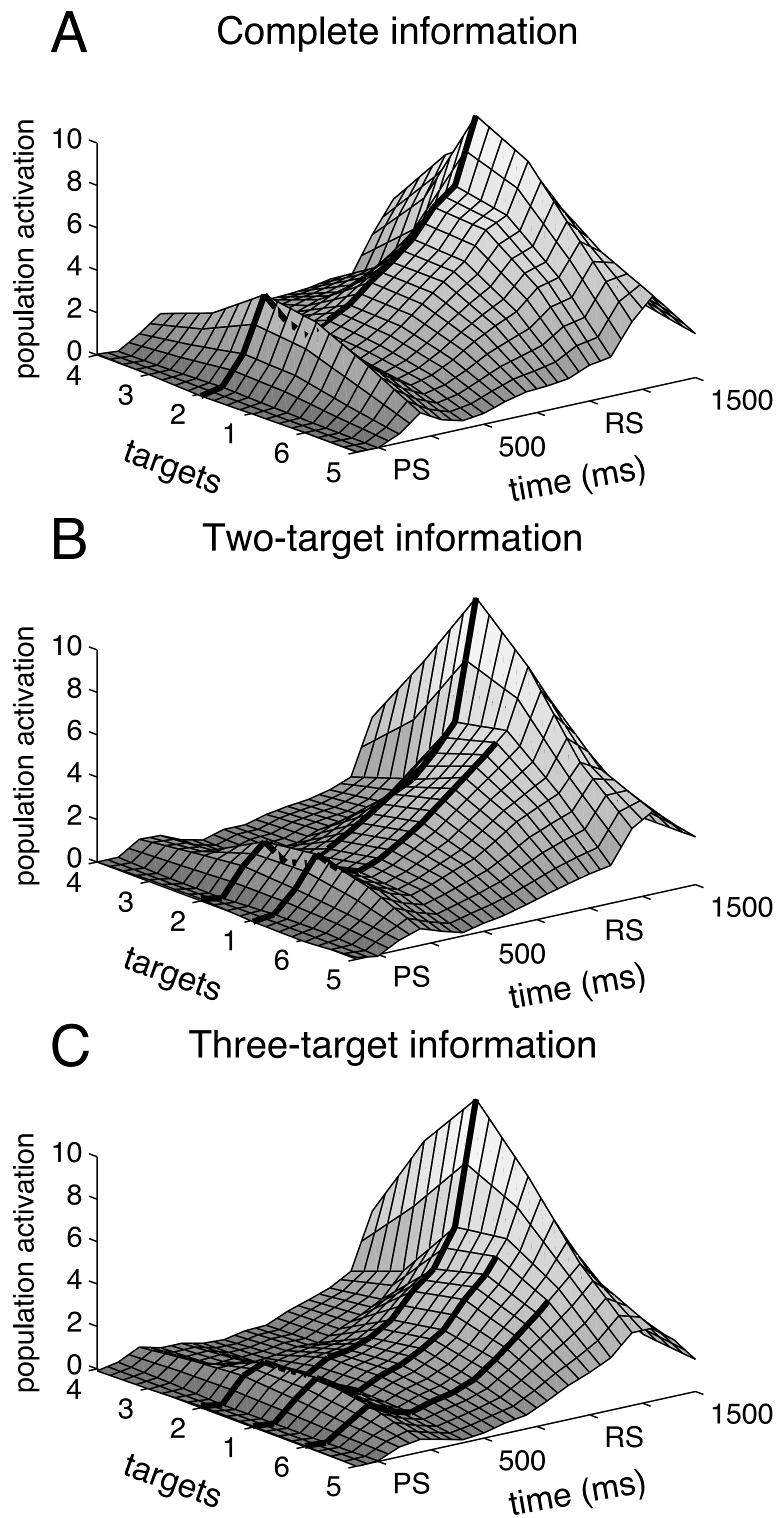


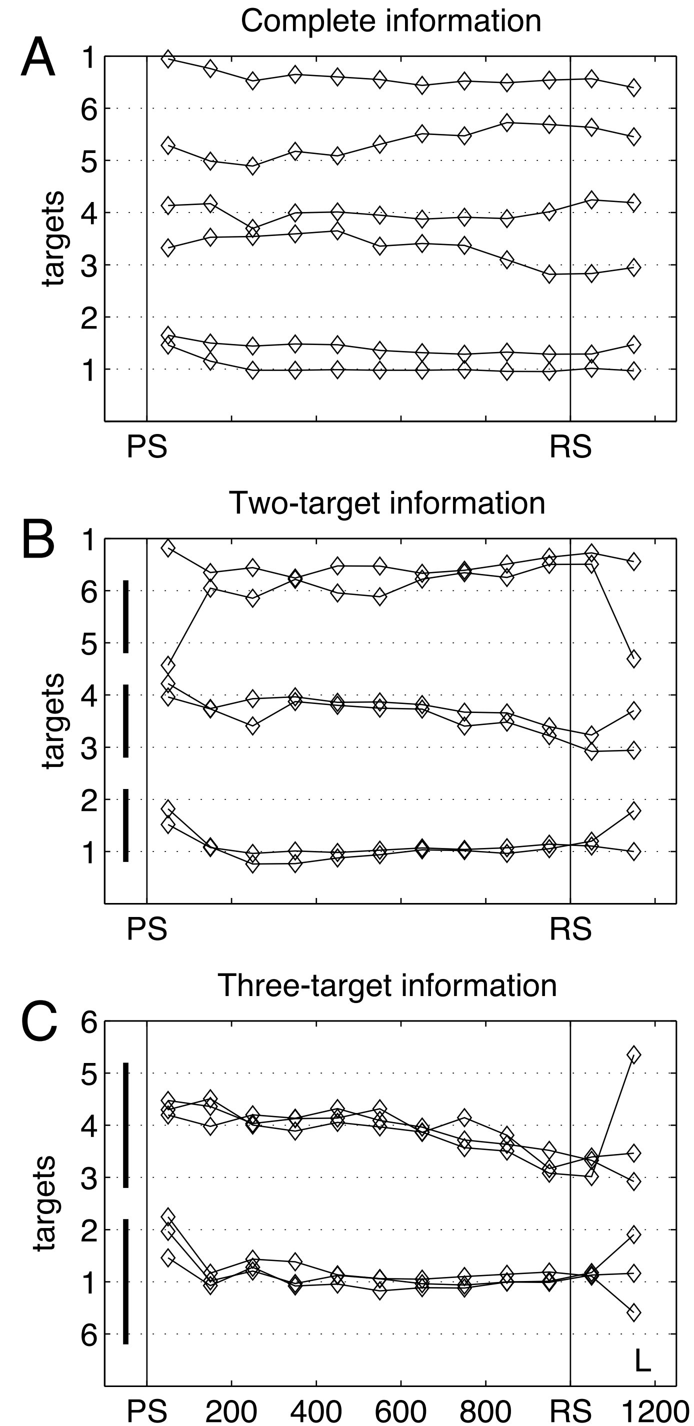
[after Bastian, Riehle, Schöner, submitted]



[Bastian, Riehle, Schöner: Europ J Neurosci 18: 2047 (2003)]

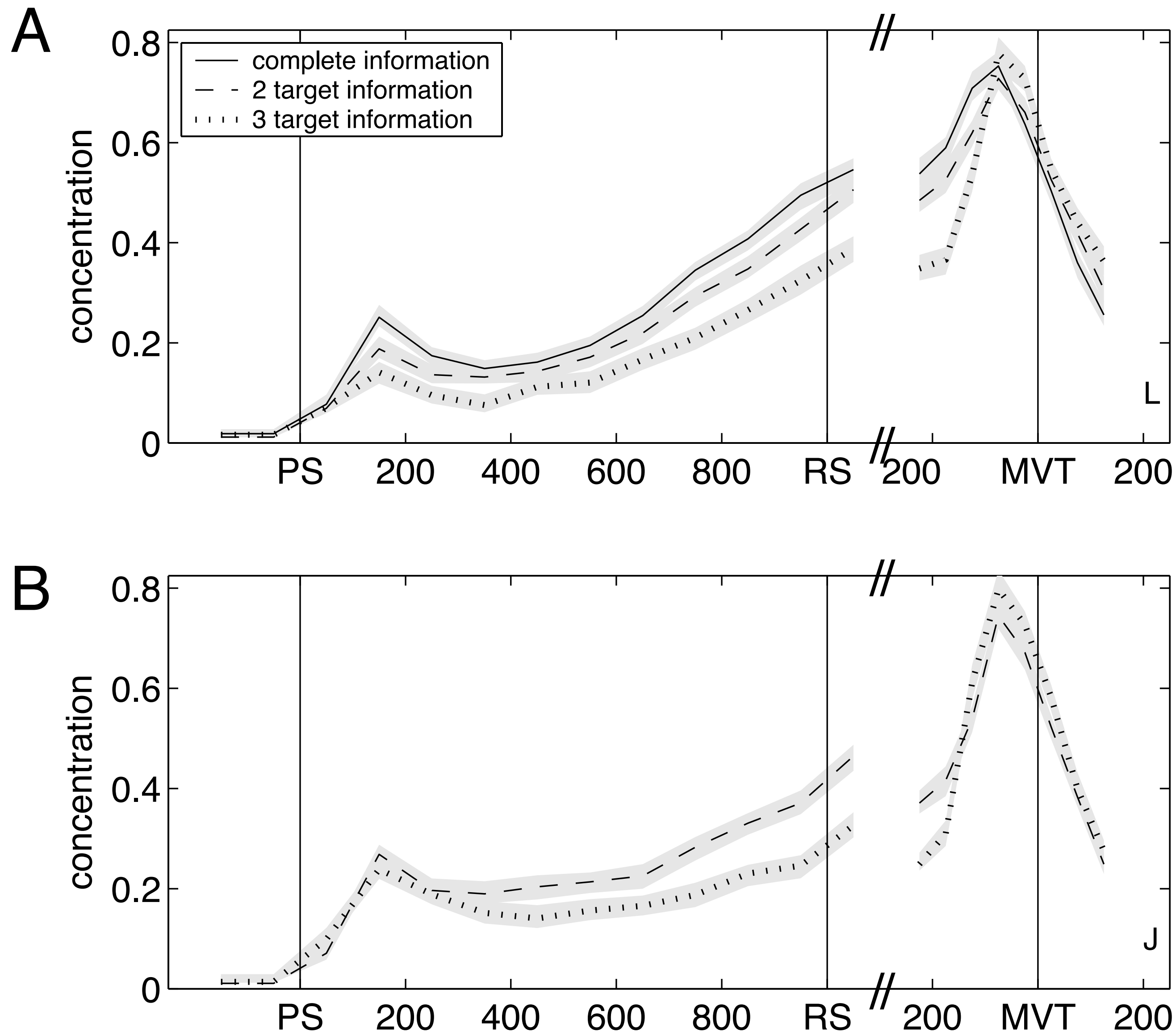
DPA reflects prior information





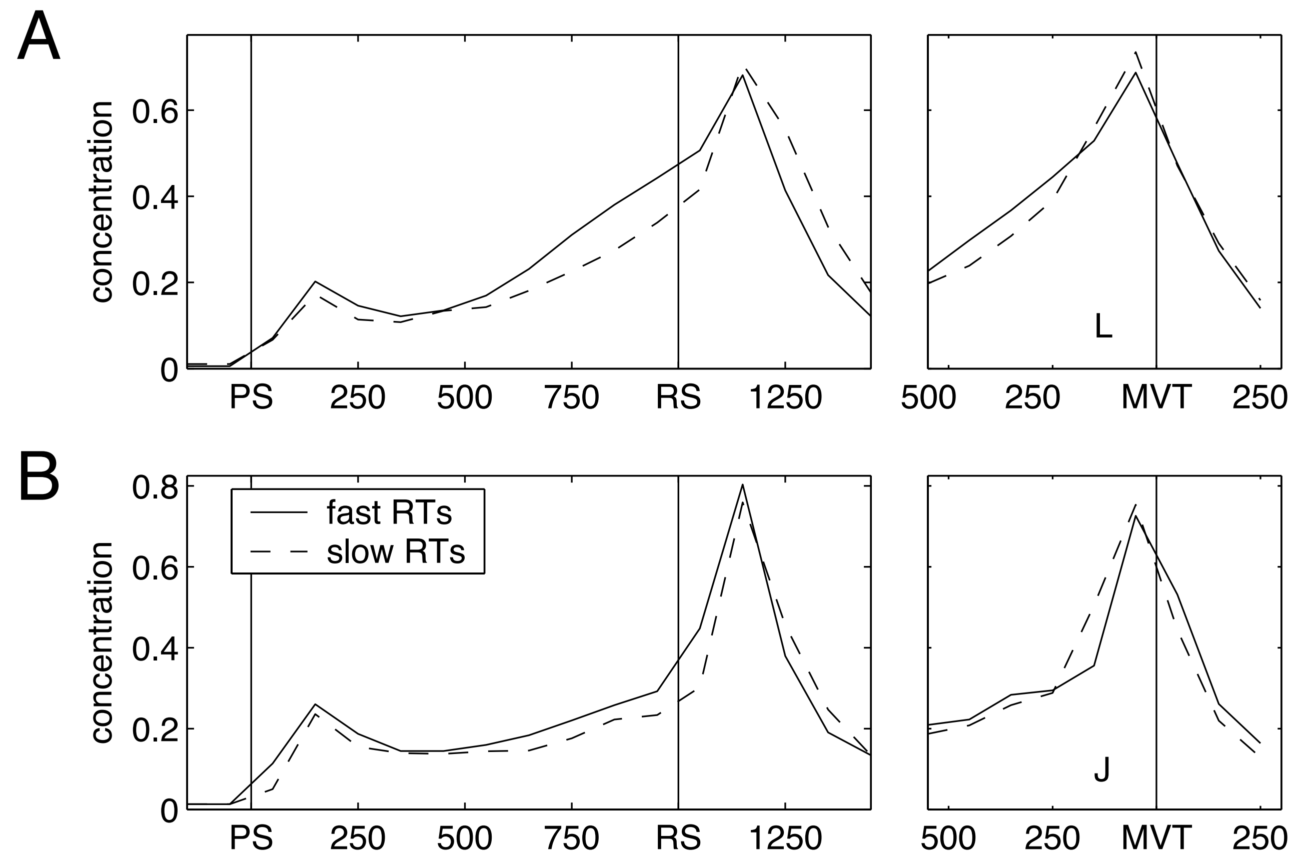
[Bastian, Schöner, Riehle 2003]

- DPA reflects prior information



[Bastian, Schöner, Riehle 2003]

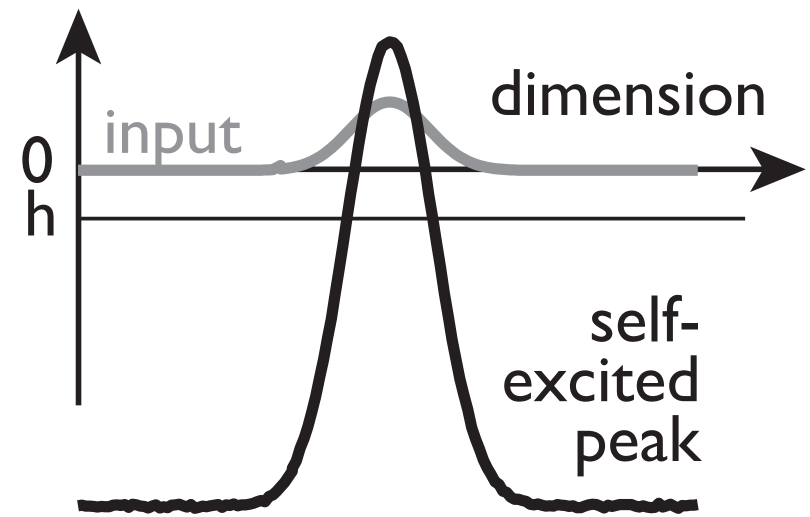
- preshape correlates with RT

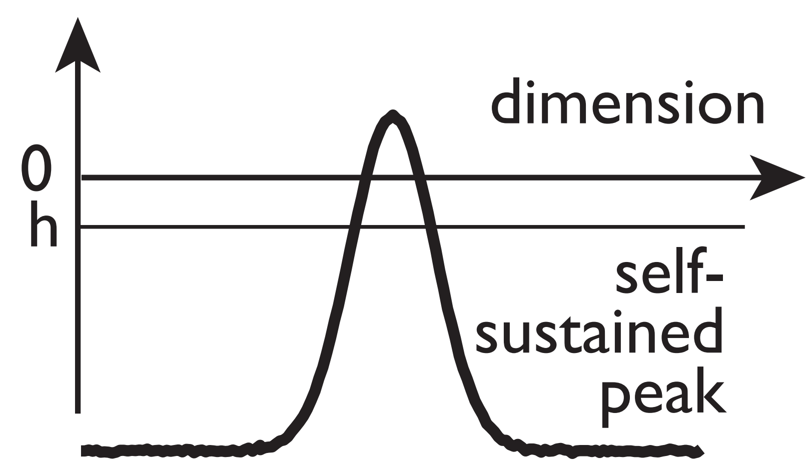


[Bastian, Schöner, Riehle 2003]

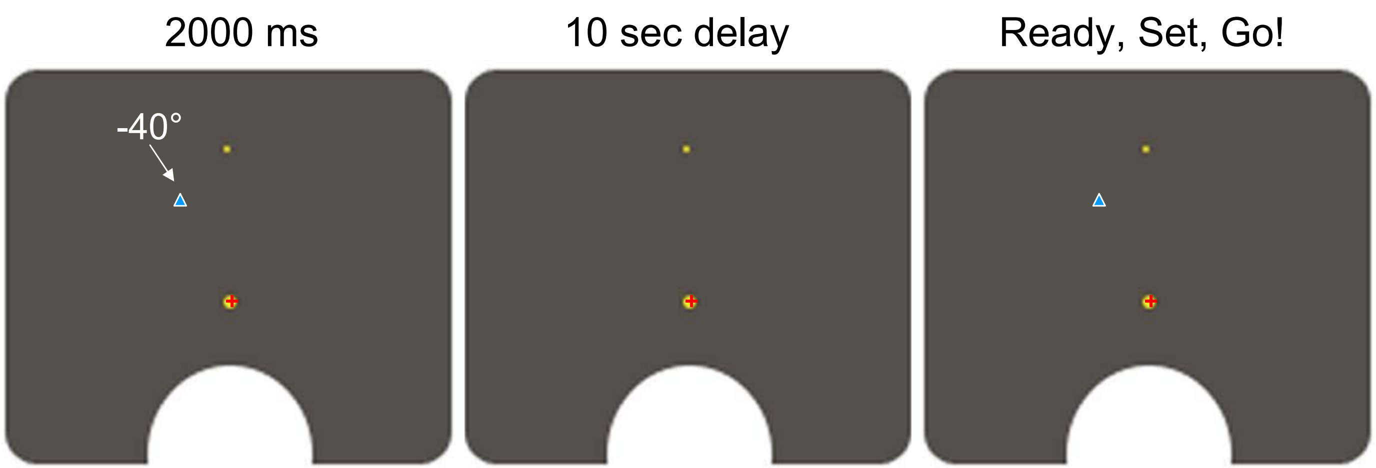
Working memory

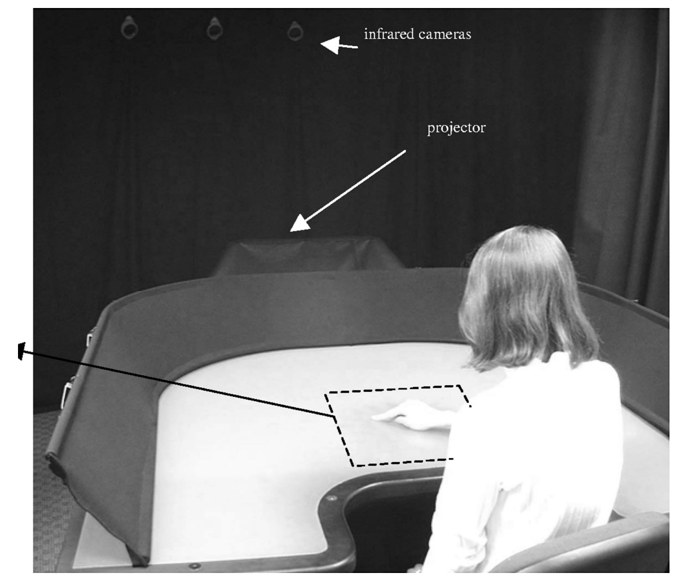
- in decision making, graded influences are seen in the fast/early time course
- working memory probes the opposite limit-case: graded influences are seen in the long run after imperative input is removed



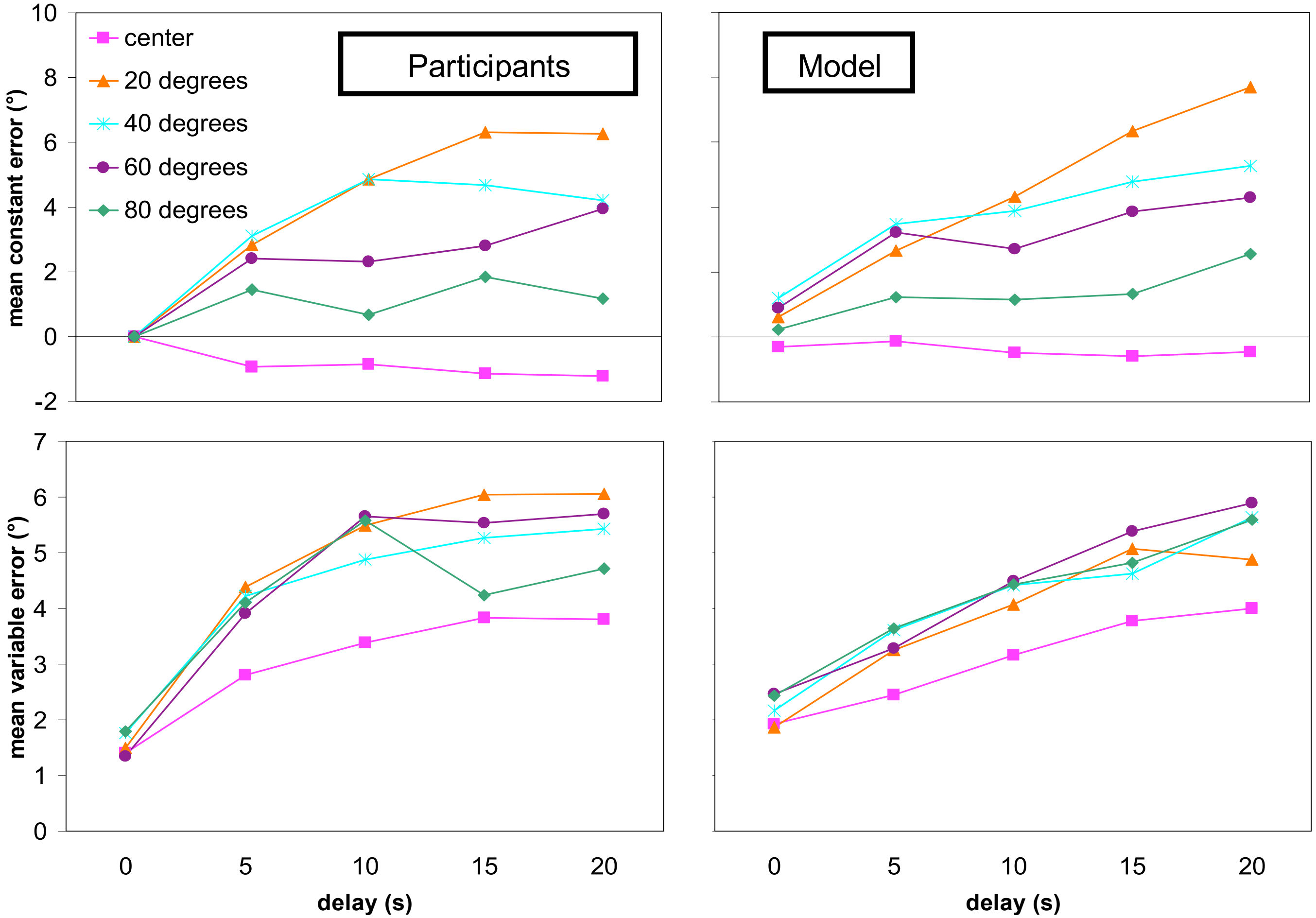


John Spencer's "space ship" task probing spatial working memory

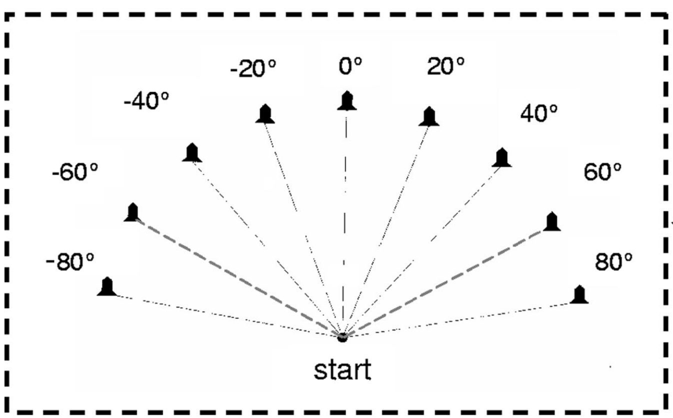


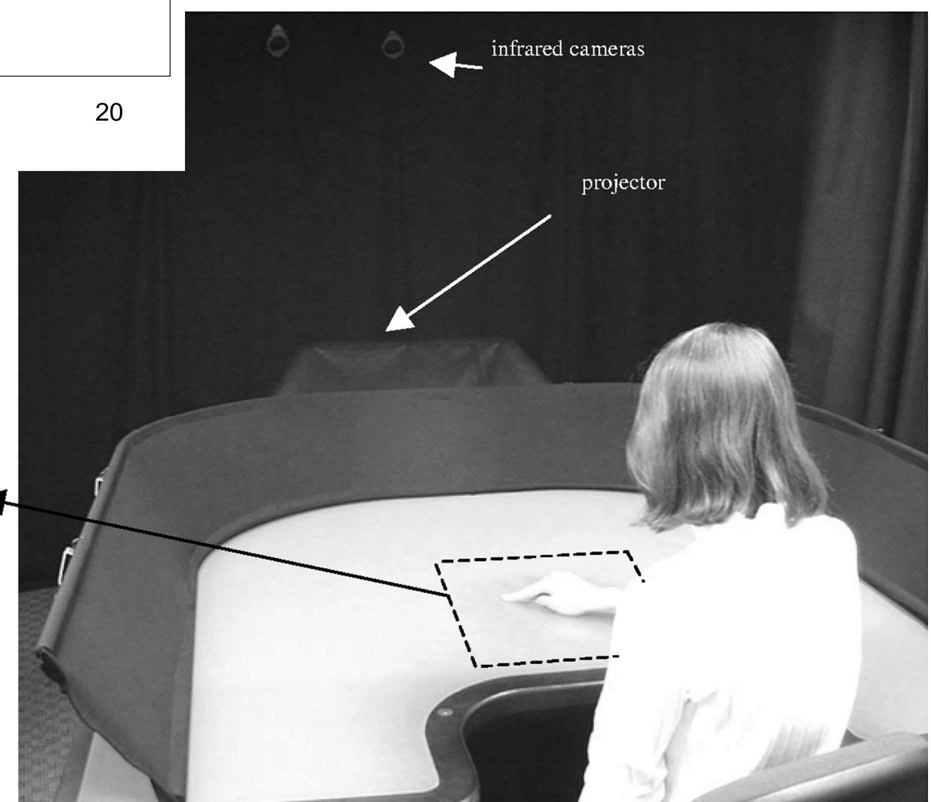


[Schutte, Spencer, *JEP:HPP* 2009]



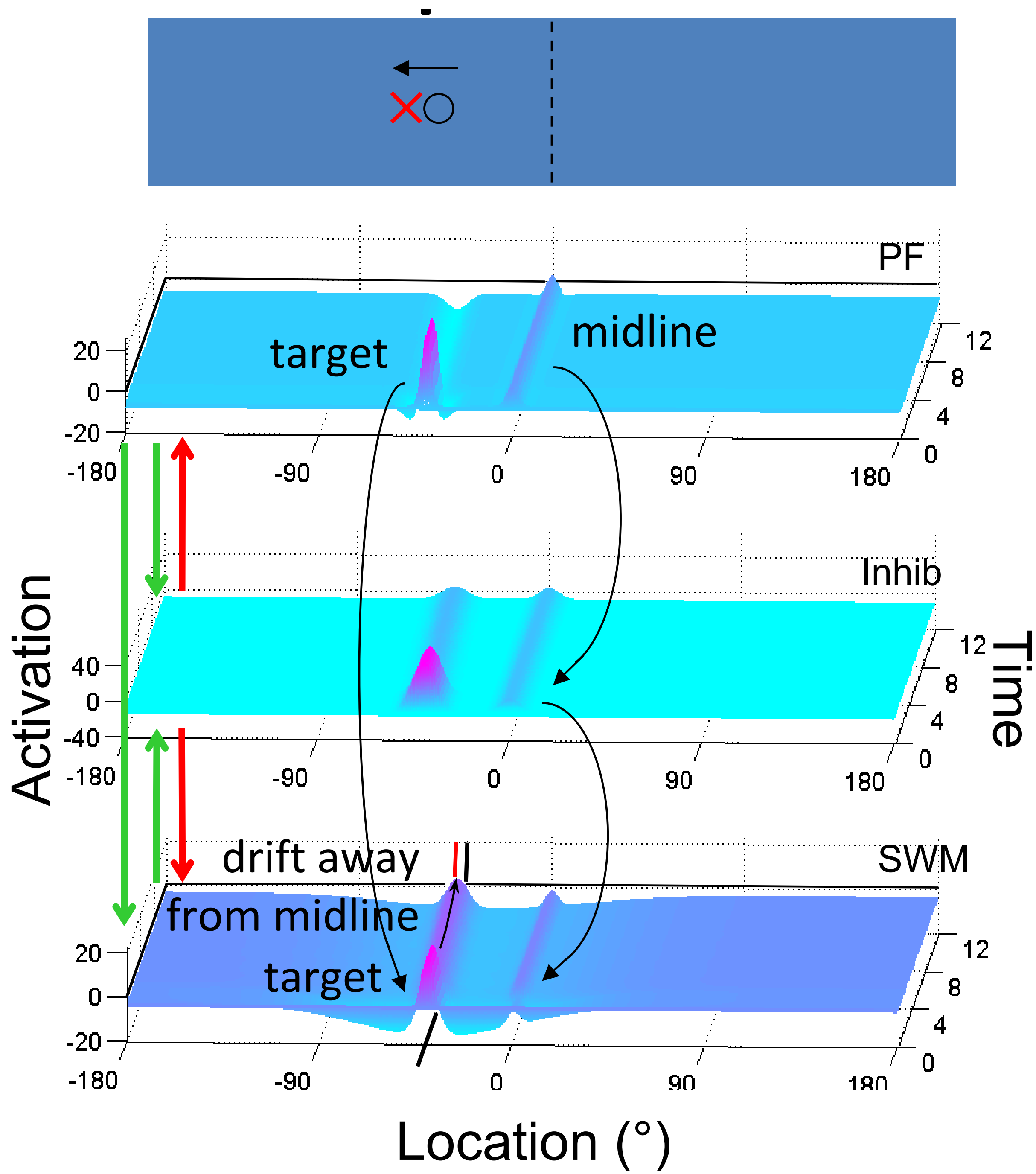
repulsion from mid-line





[Spencer, Schöner, 2006]

- DFT account of repulsion: inhibitory interaction with peak representing landmark



[Simmering, Schutte, Spencer: Brain Research, 2007]

Working memory as sustained peaks

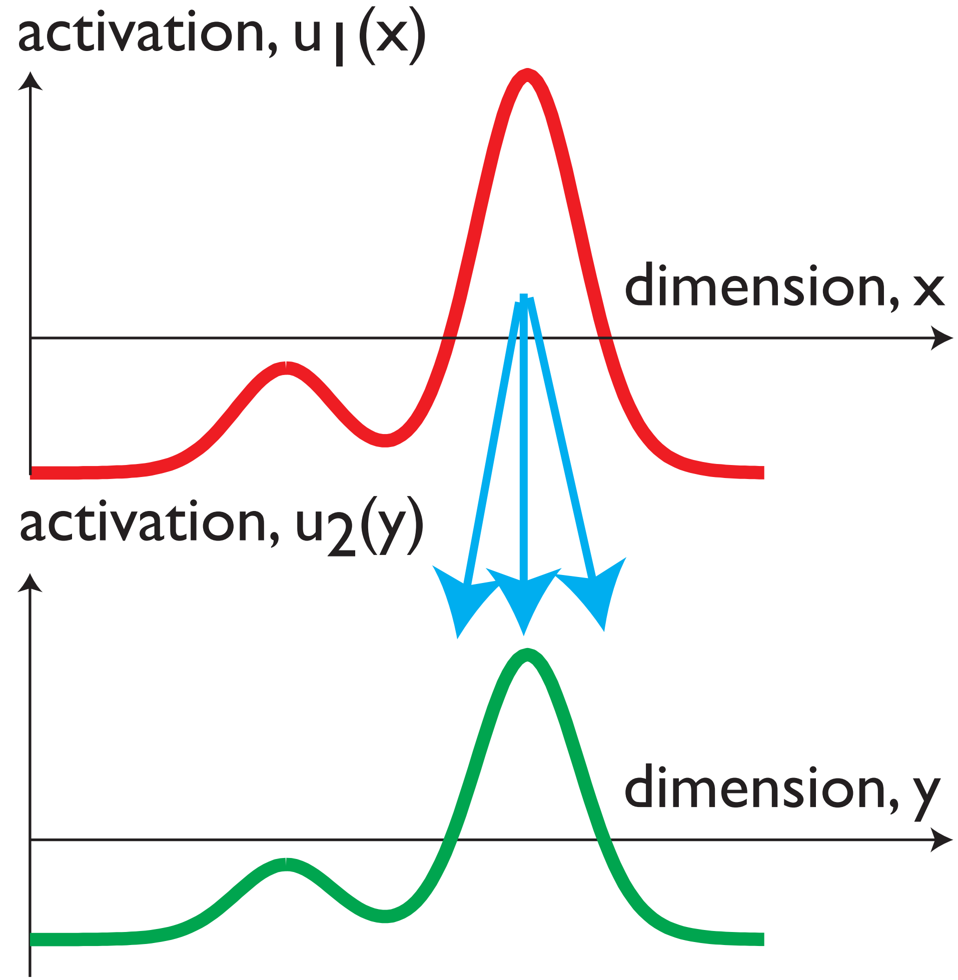
- implies metric drift of WM, which is a marginally stable state (one direction in which it is not asymptotically stable)
- => empirically real.. see extensive work
  - Johnson, J. S., Simmering, V. R., & Buss, A. T. (2014). Beyond slots and resources: Grounding cognitive concepts in neural dynamics. Attention, Perception, and Psychophysics, 76(6), 1630–1654.
  - Simmering, V. R. (2016). Working Memory Capacity in Context: Modeling Dynamic Processes of Behavior, Memory and Development. Monographs of the Society for Research in Child Development, 81(3), 1–158.
- => talk by Sebastian Schneegans

Learning in DFT

- Learning is change of behavior based on experience
  - experience is driven by activation patterns
  - behavior is generated by neural dynamics
- => Learning is change of the neural dynamics driven by activation patterns

Learning: Hebb

- projections among fields (or from sensory input to field) evolve according to a dynamic Hebb rule

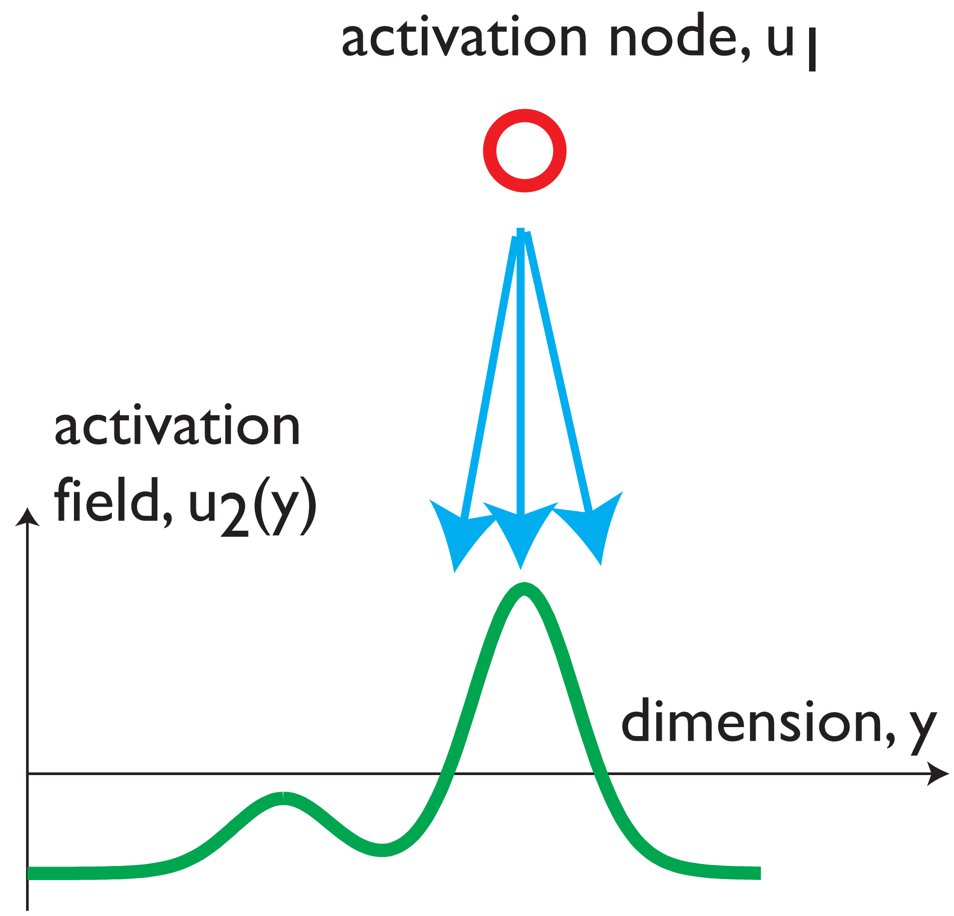


$$\tau \dot{W}(x, y, t) = \epsilon(t)\Big(- W(x, y, t) + f(u_1(x, t)) \times f(u_2(y, t))\Big)$$

[Sandamirskaya, Frontiers Neurosci 2014]

Learning: Hebb

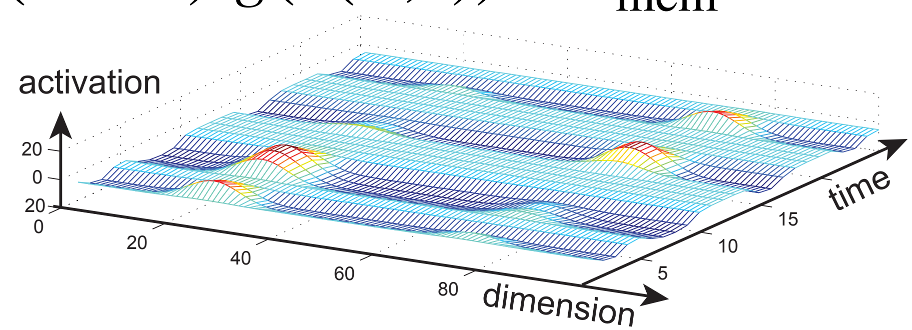
- important in DFT for projections from zero-dimensional nodes to fields
- => concepts
- => talks by Mathis Richter, Daniel Sabinasz, Jan Tekülve



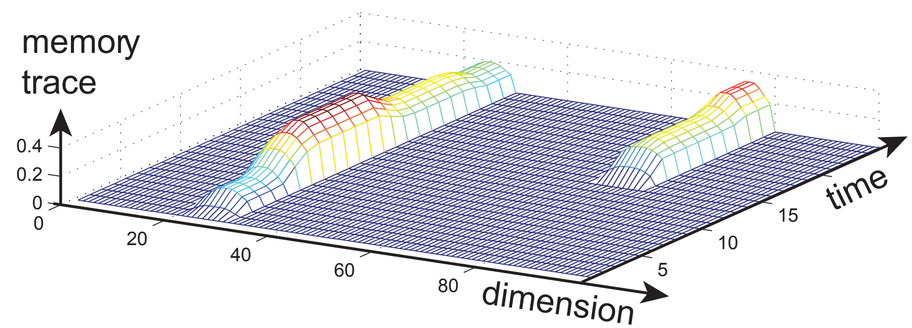
Learning: memory trace

- zero-the order Hebb ~ the bias input in NN
- amplified in the boost-driven detection instability

$$\tau \dot{u}(x,t) = -u(x,t) + h + s(x,t) + \int dx' w(x-x')\; g(u(x',t)) + u_{\mathrm{mem}}$$



$$\tau_{\mathrm{mem}} \dot{u}_{\mathrm{mem}}(x,t) = -u_{\mathrm{mem}}(x,t) + g(u(x,t))$$

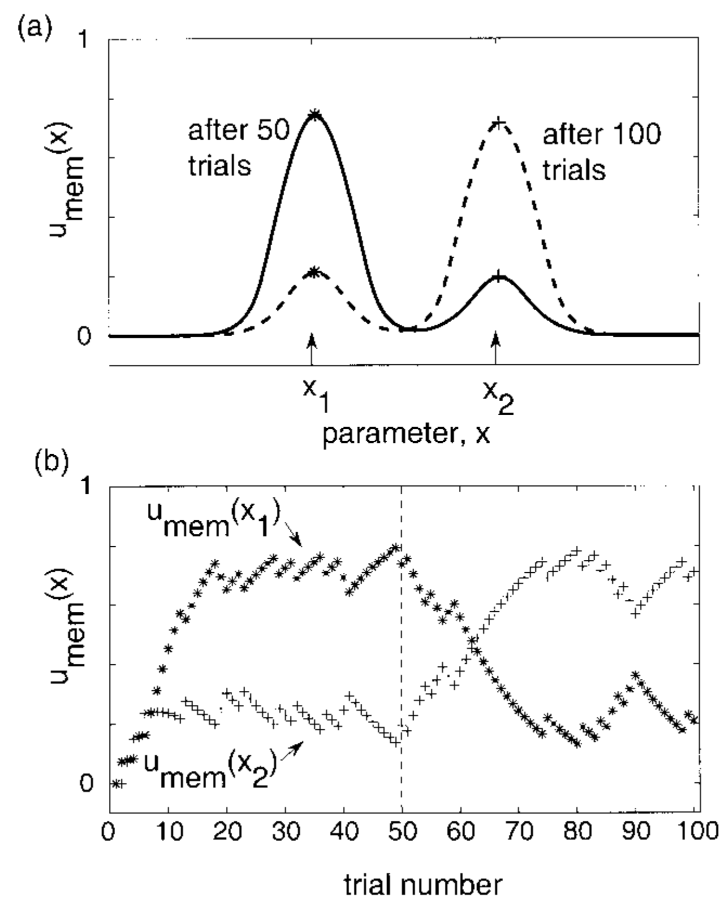


$$\tau_{\mathrm{mem}} \dot{u}_{\mathrm{mem}}(x,t) = 0$$

if there is no supra-threshold activation anywhere in the field

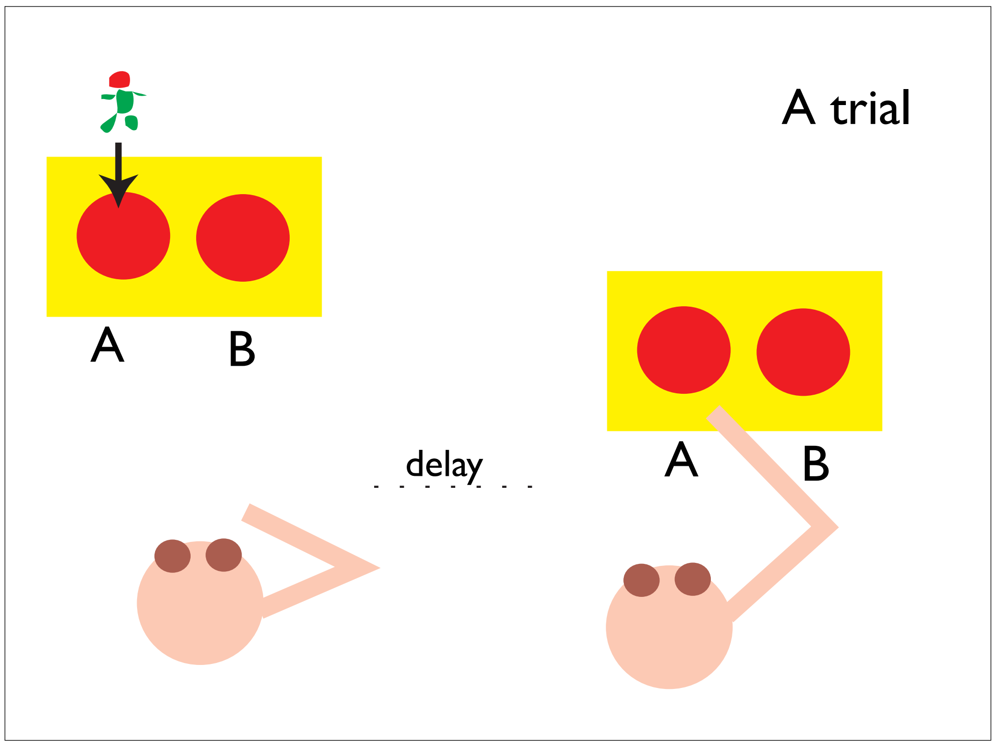
Learning: memory trace

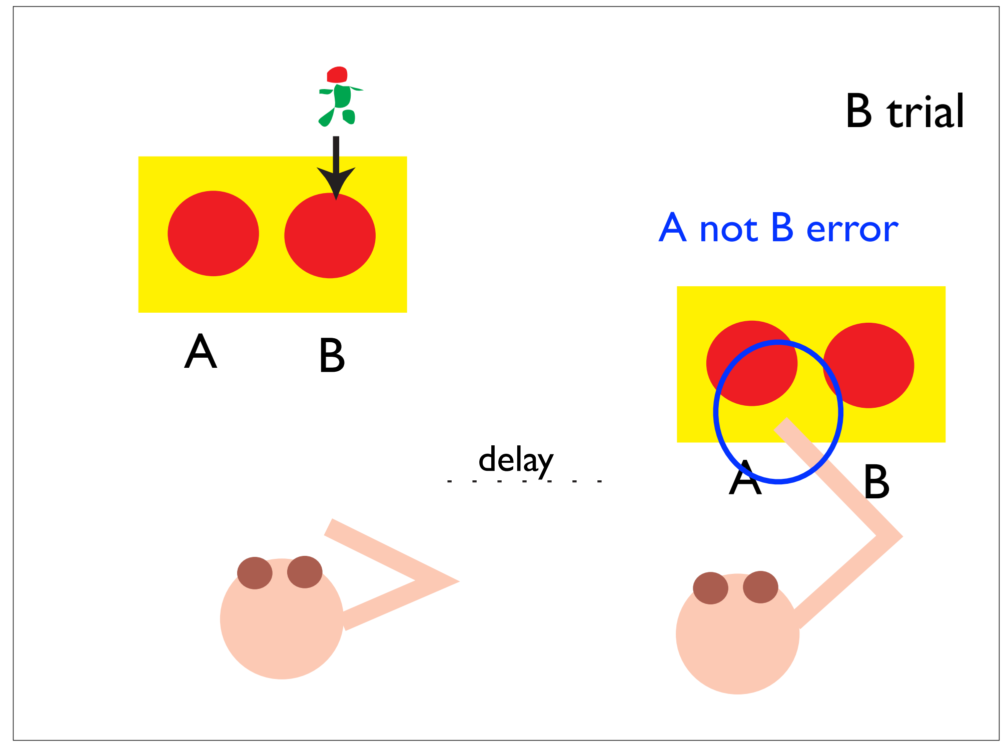
- provides an account for the construction of priors… link to probabilistic thinking
- example: Hyman law from the frequency of choices



[Erlhagen, Schöner, *Psych Rev* 2002]

Piaget's A not B paradigm: "out-of-sight -- out of mind"

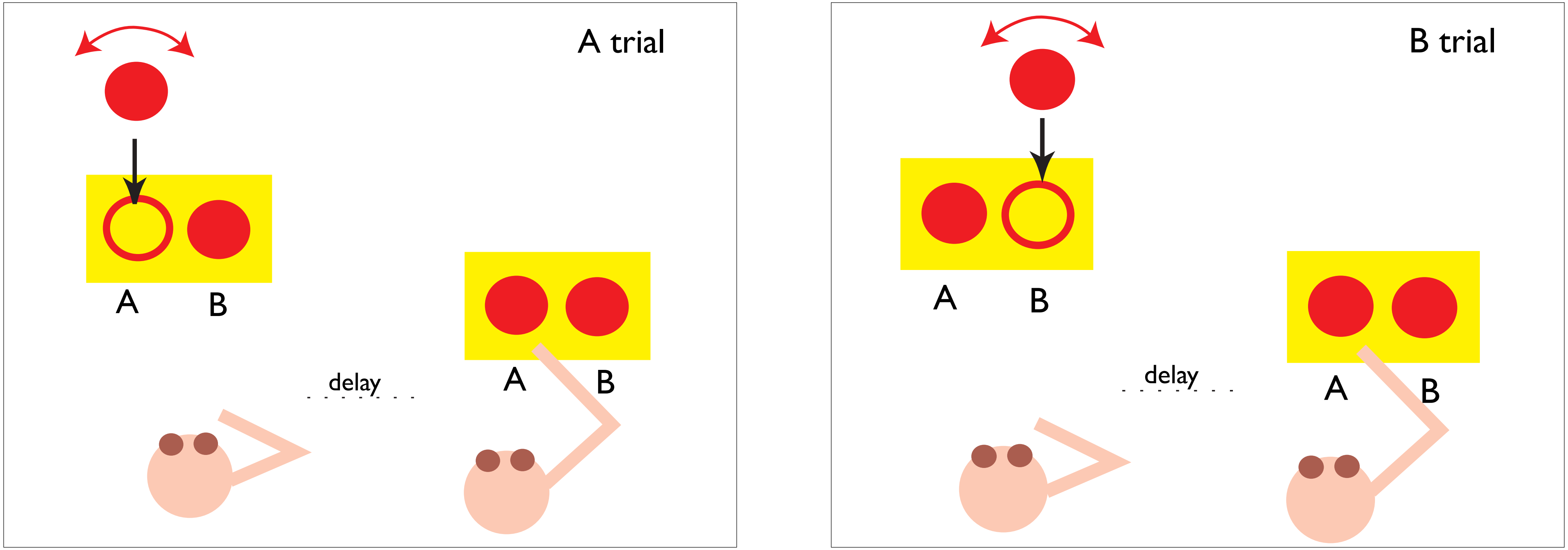




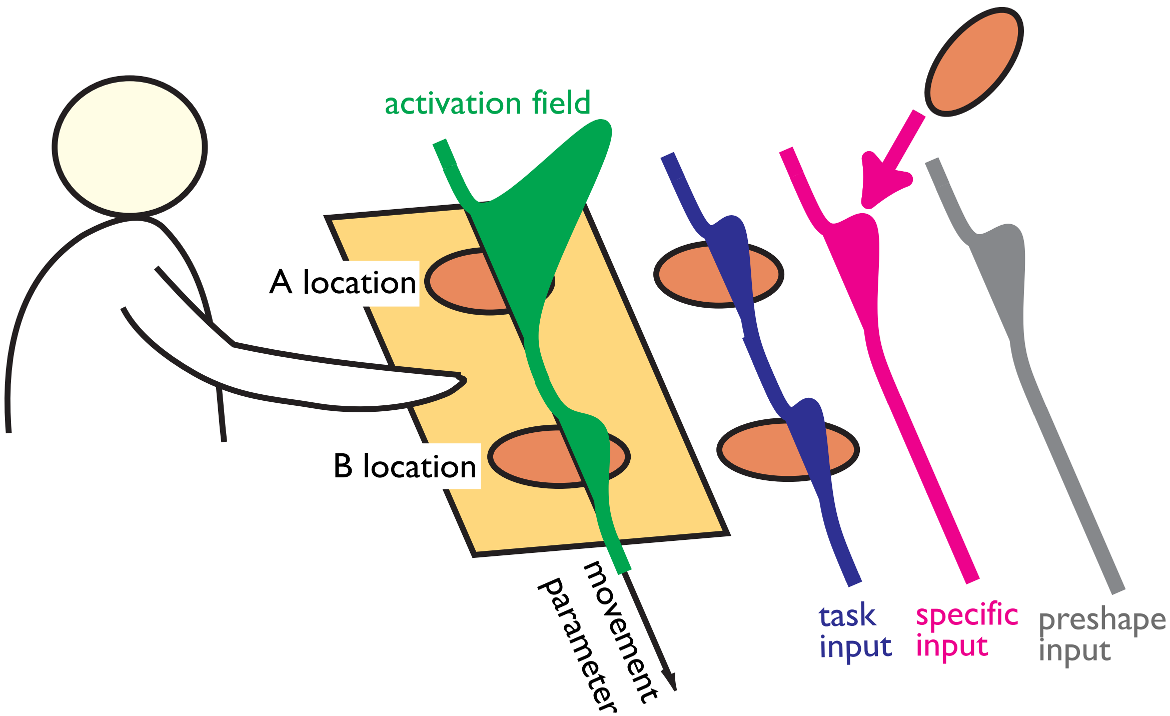
Toyless variant of A not B task

[Smith, Thelen et al.: Psychological Review (1999)]

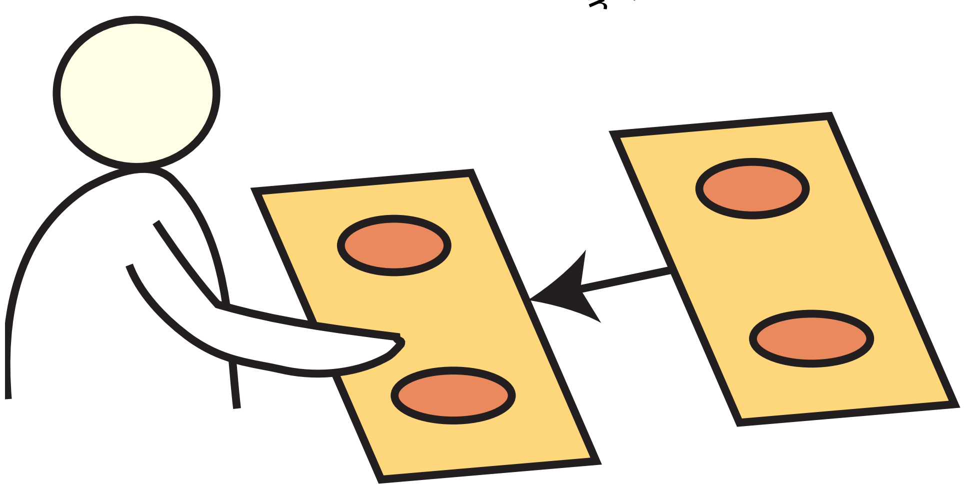
Toyless variant of A not B task reveals that A not B is essentially a decision task!



[Smith, Thelen et al.: Psychological Review (1999)]



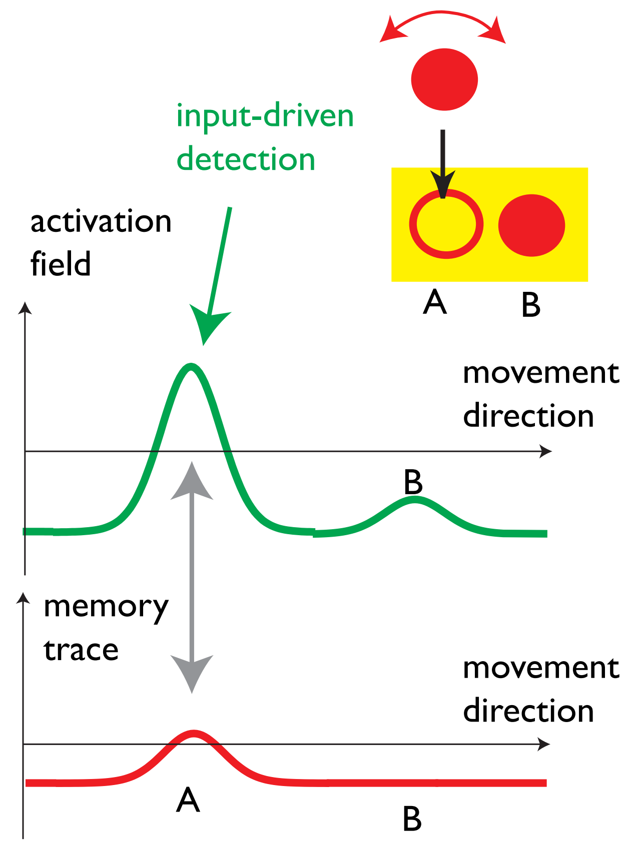
[Thelen, et al., BBS (2001)]



[Dinveva, Schöner, Dev. Science 2007]

Instabilities

- detection: forming and initiating a movement goal
- selection: making sensori-motor decisions
- (learning: memory trace)
- boost-driven detection: initiating the action
- memory instability: old infants sustain during the delay, young infants do not



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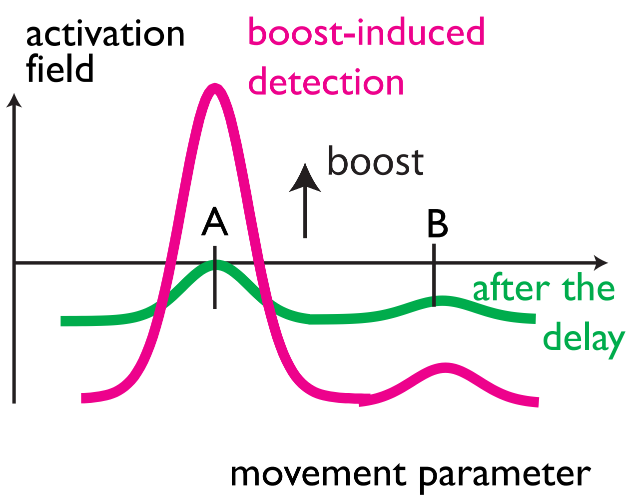

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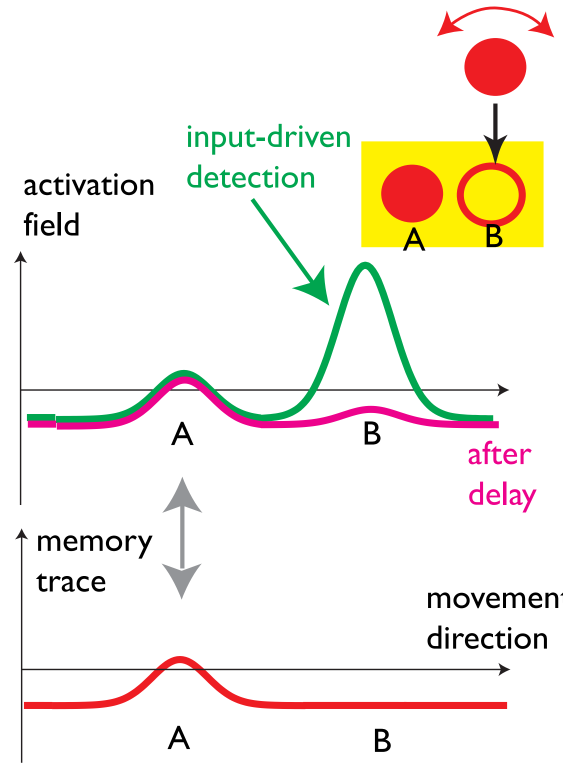
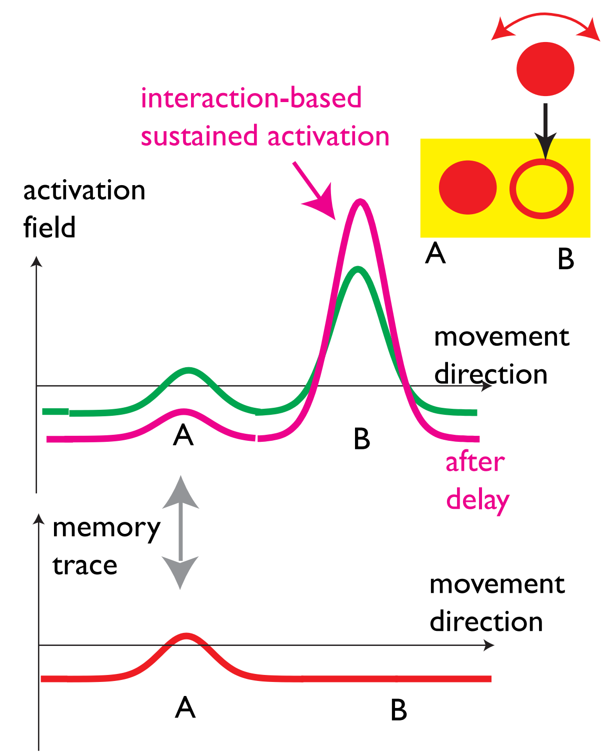
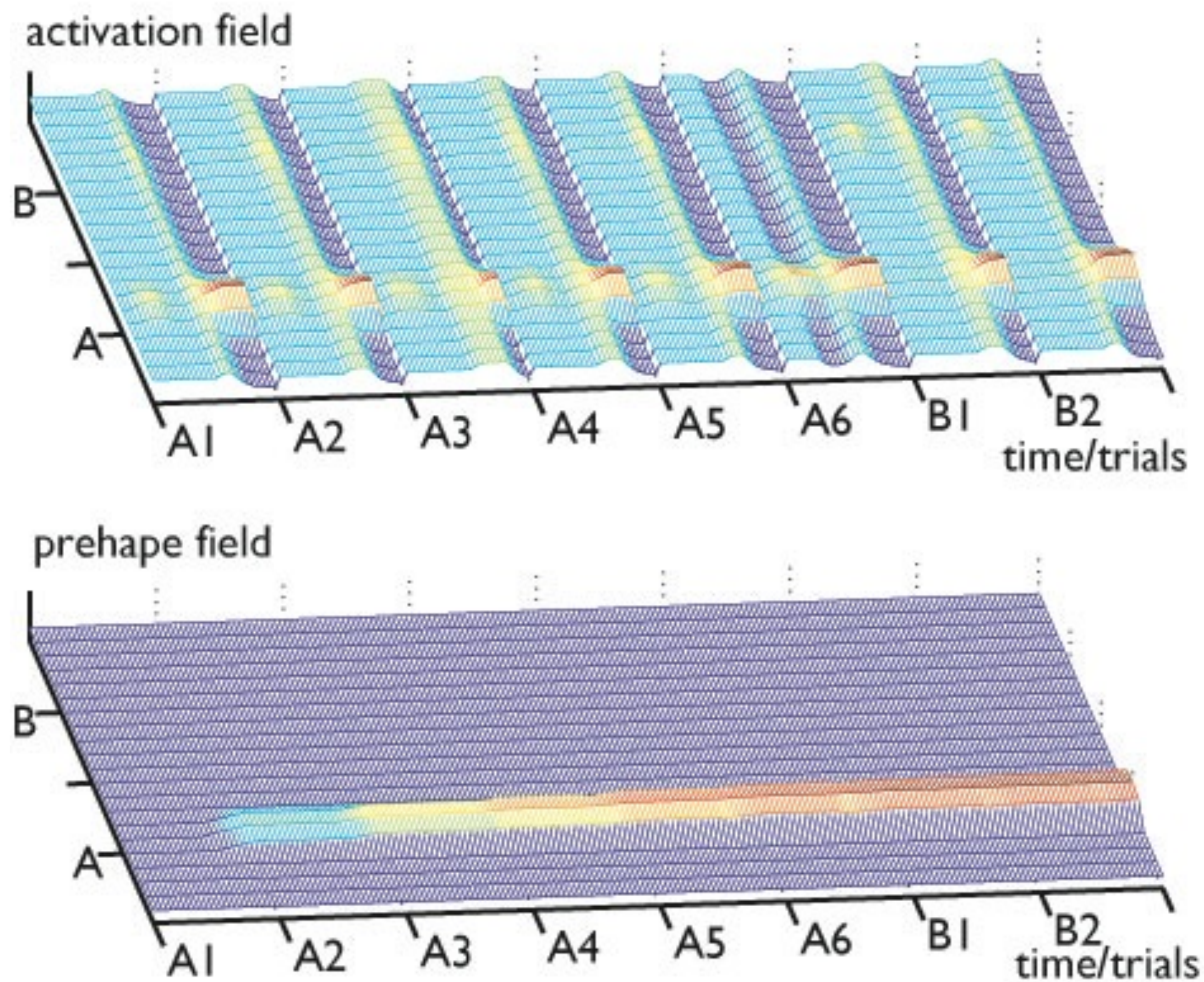
young



old

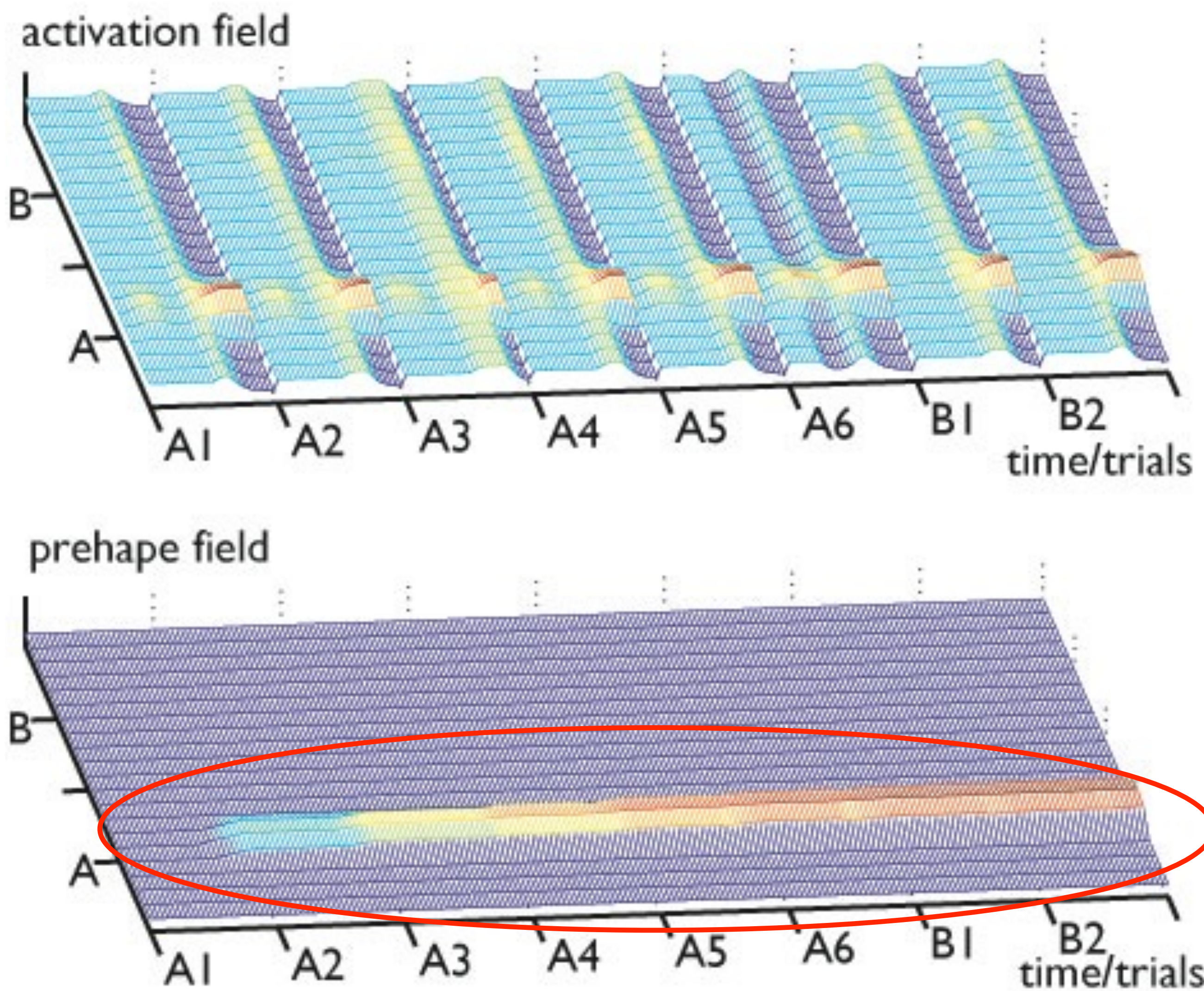


DFT of infant perseverative reaching



[Dinveva, Schöner, Dev. Science 2007]

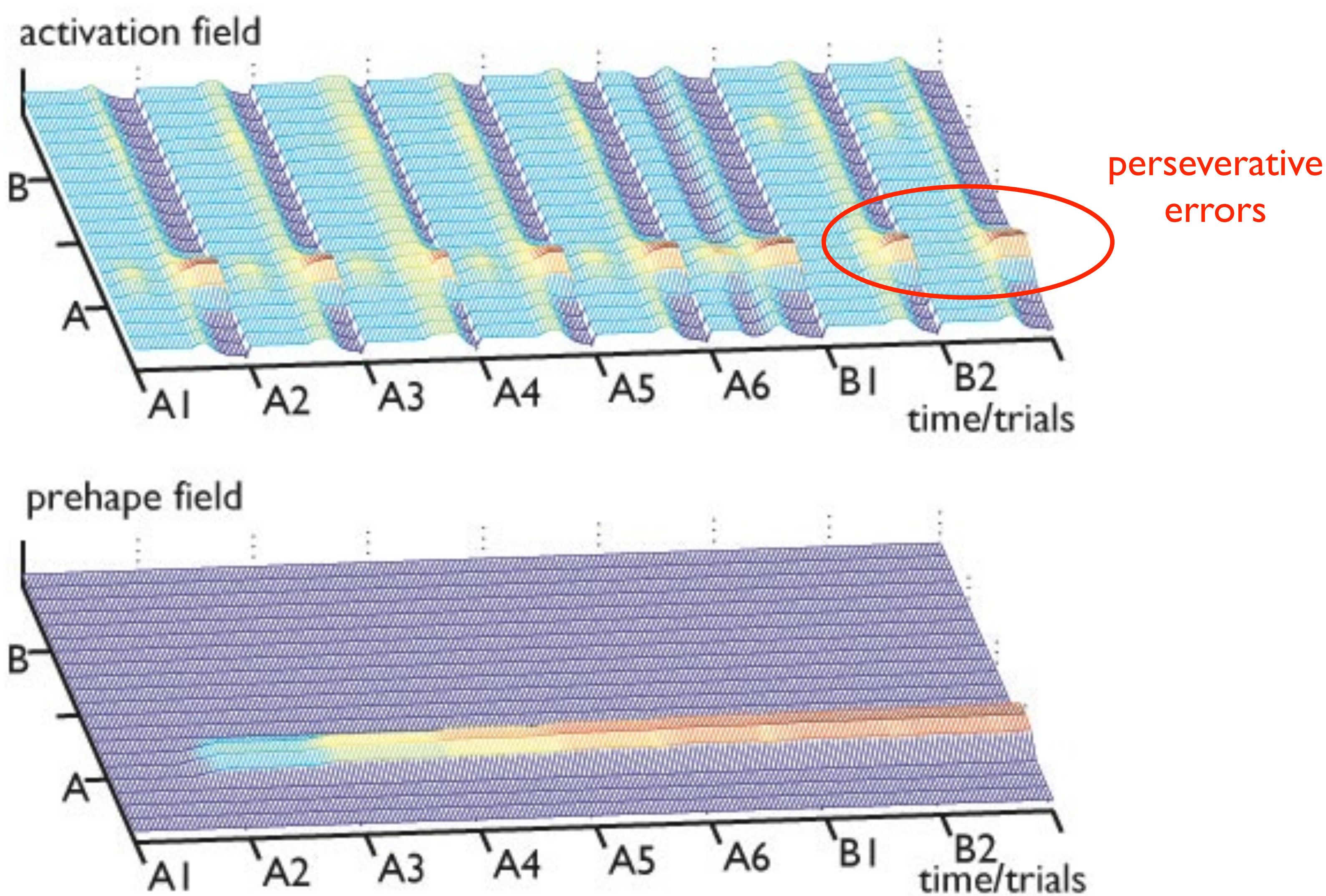
DFT of infant perseverative reaching



memory trace

[Dinveva, Schöner, Dev. Science 2007]

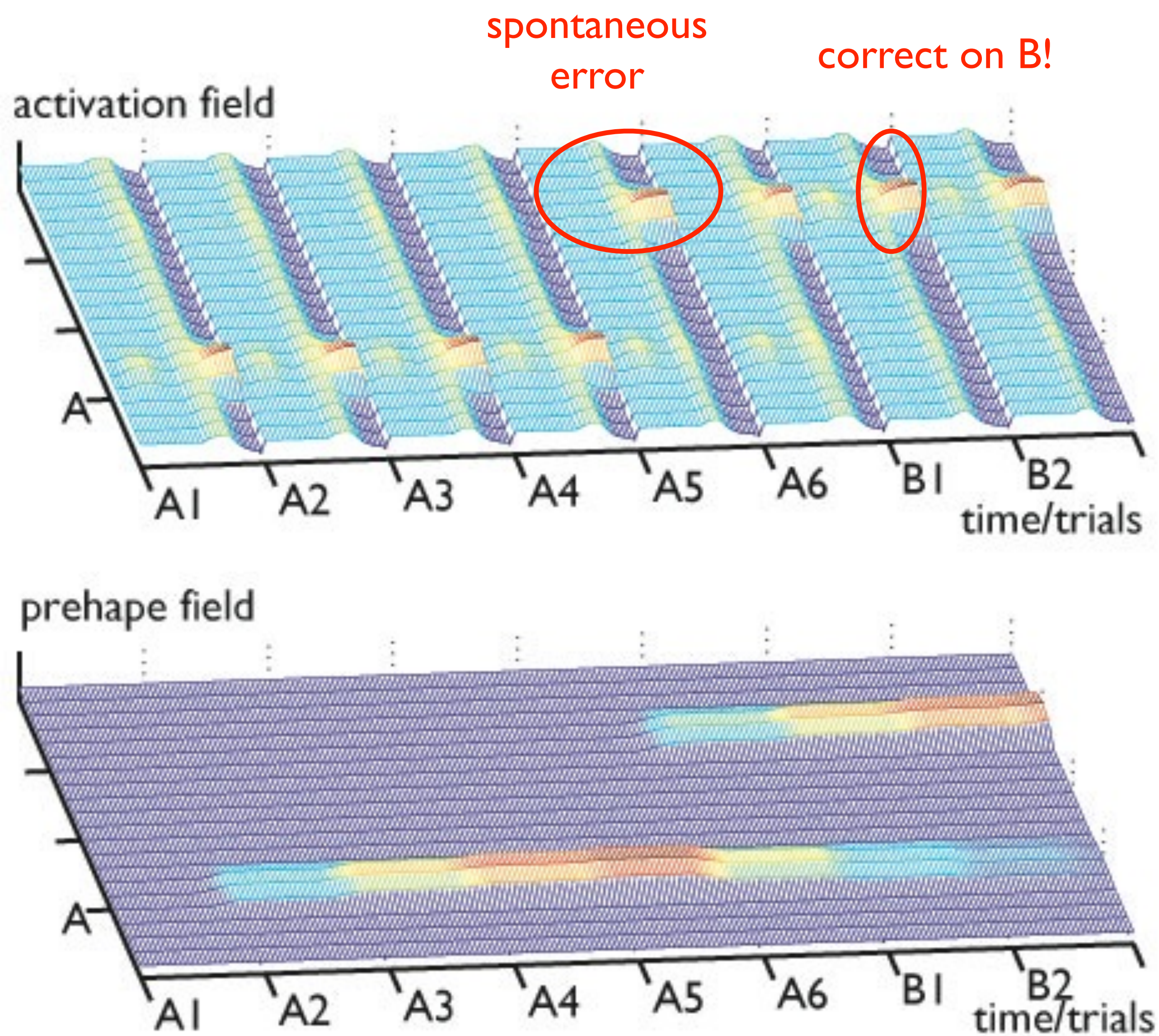
DFT of infant perseverative reaching



[Dinveva, Schöner, Dev. Science 2007]

DFT of infant perseverative reaching

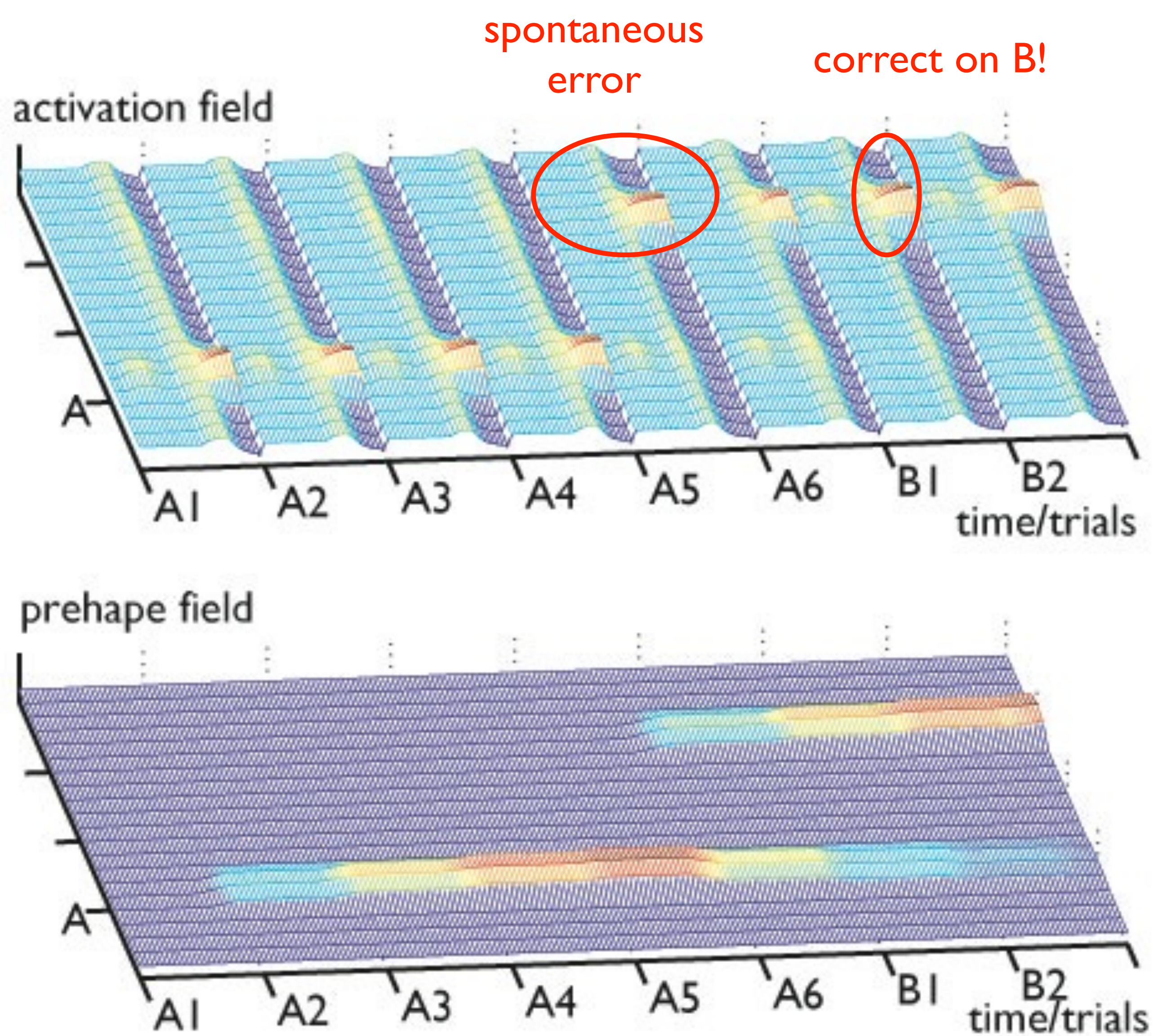
- in spotaneous errors, activation arises at B on an A trial
- which leads to correct reaching on B trial



[Dinveva, Schöner, Dev. Science 2007]

DFT of infant perseverative reaching

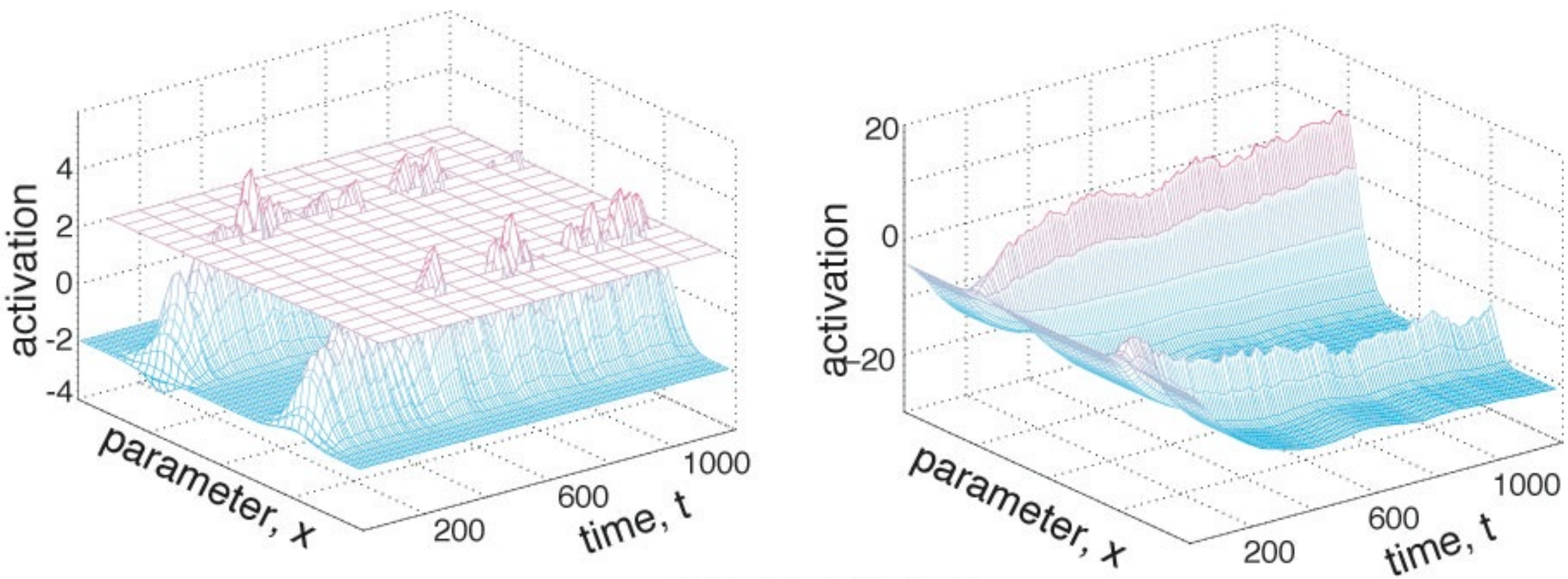
- that is because reaches to B on A trials leave memory trace at B



[Dinveva, Schöner, Dev. Science 2007]

DFT is a neural process model

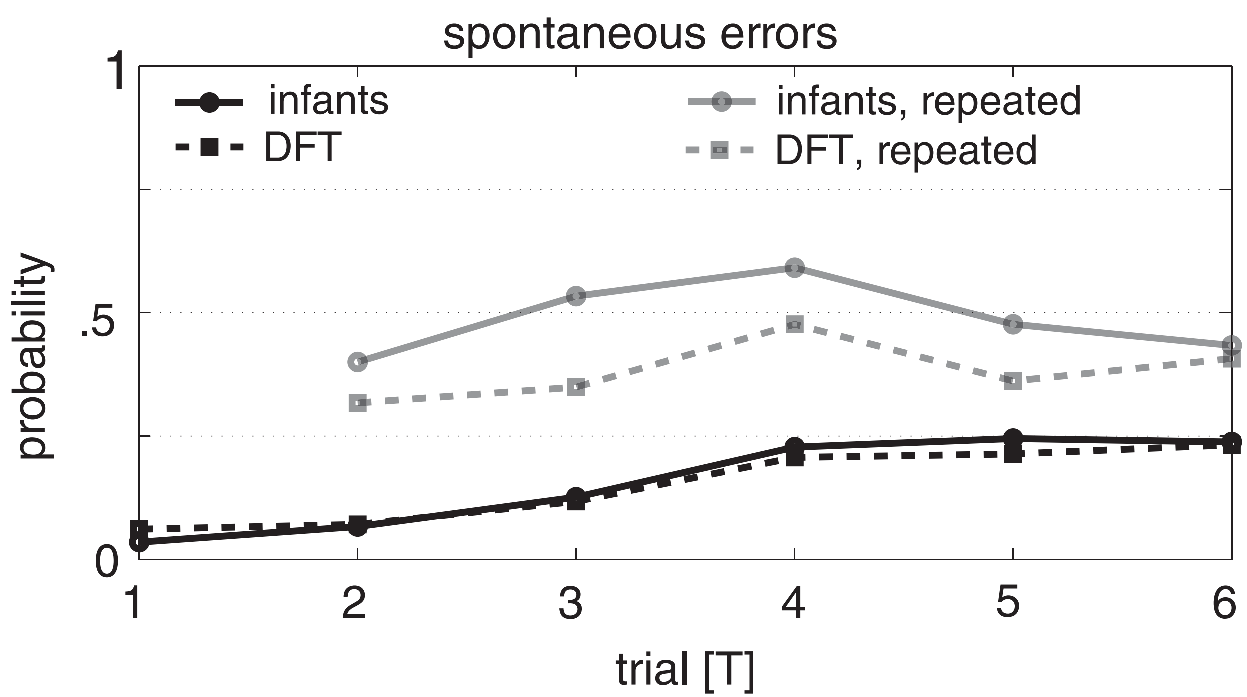
- that makes the decisions in each individual trial, by amplifying small differences into a macroscopic stable state
- and that's how decisions leave traces, have consequences



[Wilimzig, Schöner, 2006]

Decisions have consequences

- a spontaneous error doubles probability to make the spontaneous error again



[Dineva, Schöner: Connection Science 2018]

Conclusion

- DFT models of behavior by mapping experimental conditions/measures onto neural states…
- even though this interface is limited, it provides process accounts for sensorimotor cognition
- I will expand this interface when talking about "embodied DFT" next…